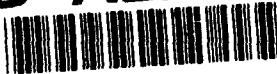


(2)

NAVAL POSTGRADUATE SCHOOL
Monterey, California

AD-A274 839



DTIC
SELECTED
JAN 25 1994
S C D

THESIS

COMPARATIVE EFFICACIES OF DECISION STRATEGIES
AND THE EFFECTS OF LEARNING
IN DYNAMIC ENVIRONMENTS:
A COMPUTER SIMULATION APPROACH

by

Spencer Rutledge III

September, 1993

Thesis Advisor:

Kishore Sengupta

Approved for public release; distribution is unlimited.

94-02114



94 1 25 011

Unclassified

Security Classification of this page

REPORT DOCUMENTATION PAGE

1a Report Security Classification: Unclassified		1b Restrictive Markings	
2a Security Classification Authority		3 Distribution/Availability of Report Approved for public release; distribution is unlimited.	
2b Declassification/Downgrading Schedule			
4 Performing Organization Report Number(s)		5 Monitoring Organization Report Number(s)	
6a Name of Performing Organization Naval Postgraduate School	6b Office Symbol (if applicable) *52	7a Name of Monitoring Organization Naval Postgraduate School	
6c Address (city, state, and ZIP code) Monterey CA 93943-5000		7b Address (city, state, and ZIP code) Monterey CA 93943-5000	
8a Name of Funding/Sponsoring Organization	6b Office Symbol (if applicable)	9 Procurement Instrument Identification Number	
Address (city, state, and ZIP code)		10 Source of Funding Numbers Program Element No Project No Task No Work Unit Accession No	
11 Title (include security classification) COMPARATIVE EFFICACIES OF DECISION STRATEGIES AND THE EFFECTS OF LEARNING IN DYNAMIC ENVIRONMENTS: A COMPUTER SIMULATION APPROACH			
12 Personal Author(s) Spencer Rutledge III			
13a Type of Report Master's Thesis	13b Time Covered From To	14 Date of Report (year, month, day) 1993 September 15	15 Page Count 62
16 Supplementary Notation The views expressed in this thesis are those of the author and do not reflect the official policy or position of the Department of Defense or the U.S. Government.			
17 Cosati Codes	18 Subject Terms (continue on reverse if necessary and identify by block number) Dynamic Decision Making, Simulation, Complexity, Decision Rules		
19 Abstract (continue on reverse if necessary and identify by block number) Models of aggregation in management science and economics are not consistent with micro-empirical knowledge of individual decision making. This has occurred as a result of using heuristics that are derived from behavioral studies which focused on discrete incidents. This approach fails to recognize decision making as a continuous process and overlooks the importance of feedback. This study examines the performance of various decision strategies (heuristics) in dynamic environments through computer simulation. Within dynamic task environments, three classes of strategies are examined: (a) feedback oriented strategies, (b) nonfeedback oriented strategies and; (c) a strategy that incorporates learning. The efficacies of these strategies are compared. The results show that feedback oriented strategies achieved a higher level of performance than non-feedback oriented strategies. And the strategy that incorporated learning outperformed all other strategies. A few anomalies exist and may require additional sampling. The implications of these findings for command decision making indicate that, feedback from prior military actions can play an important role in adapting existing systems to meet new military roles in changing environments.			
20 Distribution/Availability of Abstract <input checked="" type="checkbox"/> unclassified/unlimited <input type="checkbox"/> same as report <input type="checkbox"/> DTIC users	21 Abstract Security Classification Unclassified		
22a Name of Responsible Individual Professor Kishore Sengupta	22b Telephone (include Area Code) (408) 656-3212	22c Office Symbol AS/SE	

DD FORM 1473,84 MAR

83 APR edition may be used until exhausted

All other editions are obsolete

security classification of this page

Unclassified

Approved for public release; distribution is unlimited.

Comparative Efficacies of Decision Strategies
and the Effects of Learning
in Dynamic Environments:
A Computer Simulation Approach

by

Spencer Rutledge III
Captain, United States Marine Corps
B.S., University of Francis Marion, 1985

Submitted in partial fulfillment
of the requirements for the degree of

MASTER OF SCIENCE IN INFORMATION TECHNOLOGY MANAGEMENT

from the

NAVAL POSTGRADUATE SCHOOL
September 1993

Author:

Spencer Rutledge III

Spencer Rutledge III

Approved by:

Kishore Sen Gupta

Kishore Sengupta, Thesis Advisor

Carl R. Jones

Carl R. Jones, Associate Advisor

D. R. Whipple

David R. Whipple, Chairman
Department of Administration Sciences

ABSTRACT

Models of aggregation in management science and economics are not consistent with micro-empirical knowledge of individual decision making. This has occurred as a result of using heuristics that are derived from behavioral studies which focused on discrete incidents. This approach fails to recognize decision making as a continuous process and overlooks the importance of feedback.

This study examines the performance of various decision strategies (heuristics) in dynamic environments through computer simulation. Within dynamic task environments, three classes of strategies are examined: (a) feedback oriented strategies, (b) non-feedback oriented strategies and; (c) a strategy that incorporates learning. The relative efficacies of these strategies are compared. The results show that feedback oriented strategies achieved a higher level of performance than non-feedback oriented strategies. And the strategy that incorporated learning outperformed all other strategies. A few abnormalities exist and may require additional sampling. The implications of these findings for command decision making indicate that, feedback from prior military actions can play an important role in adapting existing systems to meets new military roles in changing environments.

TABLE OF CONTENTS

I.	INTRODUCTION	1
A.	BACKGROUND	1
B.	EXPERIMENTAL TOOL	2
C.	RESEARCH QUESTION	8
D.	CONTRIBUTION	9
II.	THEORETICAL PREMISE	10
A.	DYNAMIC DECISION MAKING	10
B.	STATIC VS DYNAMIC DECISION ENVIRONMENTS	11
C.	HOW DYNAMIC DECISION CAN BE STUDIED	12
D.	IMPORTANCE OF FEEDBACK	14
1.	Judgmental Accuracy	14
2.	Commitment	15
E.	HYPOTHESIS	16
III.	METHOD	18
A.	TASK ENVIRONMENT	18
1.	Dynamic Decision Task	18
2.	Decision Environment	19
3.	Decision Strategies	21
4.	Dependent Measures	24
B.	CONDUCT OF THE EXPERIMENT	25

IV. RESULTS	27
A. EXPERIMENTAL RESULTS	27
V. CONCLUSIONS	40
A. SUMMARY OF RESULTS	40
B. SYSTEMS THAT INCORPORATE LEARNING	41
C. LIMITING FACTORS TO GENERALIZABILITY	42
D. FUTURE RESEARCH	42
APPENDIX	44
LIST OF REFERENCES	52
INITIAL DISTRIBUTION LIST	55

DTIC QUALITY INSPECTED 5

Accession For		
NTIS	CRA&I	<input checked="" type="checkbox"/>
DTIC	TAB	<input type="checkbox"/>
Unnumbered		<input type="checkbox"/>
Jacketed		<input type="checkbox"/>
By _____		
Distribution / _____		
Avail Date _____		
Dist	Avg Date for Special	
A-1		

I. INTRODUCTION

A. BACKGROUND

A major concern in research on decision making has been the use of heuristics. Behavioral decision studies have identified heuristics in a wide variety of decision making context. Models utilizing heuristics tend to work well in some setting and provide dysfunctional consequences in others. Presently, there is no available evidence to explain these systematic errors or identify the general conditions under which heuristics perform well. Because heuristics are organizational strategies that humans devise to deal with inadequacies, researchers have focused their attention on decision makers' limited information processing system. These limitation have significant consequences in a complex decision environments. Understanding how decision makers continuously adapt to complex changing environments requires careful consideration of the structure of the environment, especially defining the role of feedback. One strategy for assessing the quality of human decision making is the use of simulation techniques to measure the performance of various decision strategies (heuristics) and their sensitivity to variations in task structure (Kleinmuntz, 1985).

B. EXPERIMENTAL TOOL

Computer simulation modeling makes it possible to study dynamic decision problems. Because dynamic environments are characterized by continual changes, both autonomously and as a result of the decision maker's action and real time decision, conventional means of studying decision making are no longer feasible. A viable alternative recognized for sometime now (Simon, 1969), is the use of simulation modeling which is well suited to represent complexity, feedback, nonlinearity, and time lags (Sterman, 1987).

Computer modeling is the programming of a computer to imitate the dynamic behavior of a real or hypothesized system in all relevant aspects. Simulation is the development and use of models to aid in the evaluation of ideas and the study of dynamic systems or situations (McLeod, 1989).

The computer simulation model used in this experiment was designed to perform the task in a way that fits currently available data about human behavior. The structure of the simulation models contain two distinct components that interact with each other;

1. The decision environment which is constructed using difference equations and
2. The decision processes of individuals modeled by:
 - a. Default strategies commonly used in studies of behavioral decision making or
 - b. Decision strategies that incorporate a learning mechanism such as statistical techniques.

The decision environment captures the physical and institutional structure of a system and is often accurately portrayed. Such environment may reflect the flow network of information, stock market activities, etc. The decision process or decision rules corresponds to the behavior of the individual actor and is often difficult to represent. Two primary sources that assist in establishing baseline decision rules are the results from behavioral decision studies (heuristics) and empirical data.

The dimensions proposed by Brehmer and Allard (1991a) to describe dynamic tasks and guide experimentation were used as a reference when designing the model. Complexity, difficulty, randomness, feedback quality, feedback delays, and strategies were factors considered.

Complexity is a relative concept that focuses primarily on control and is defined in relation to the subject's cognitive capacity. Since an underlining limitation in humans is the number of system elements and their relations that can be handled at one time, it is reasonable to define complexity in terms of system elements and their relations (Brehmer, 1991b).

Difficulty of the environment is often viewed as a derivative of complexity. However, there is no simple direct correlation between the number of elements of a system and the difficulty of the environment. For instance, in a complex system with many elements and interconnections

between elements, only a few may be relevant to the present decision. As a result, the level of difficulty may be low even though the level of complexity is high. However, from a continuous perspective, difficulty can be assessed in terms of gains and losses. Gains can be viewed as a means of increasing available options, whereas losses can be viewed as restrictive. And since losses are weighted more heavily than gains (Kahneman and Tversky, 1979; 1981) difficulty can be incorporated through the use of severe penalty functions levied on the quality of decisions. For example, when investing in mutual funds, growth funds would appear very attractive because of the potentially high yield on investment. But when considering the level of risk (penalty function) associated with achieving that potentially high yield, the investment decision becomes more difficult to make.

Random variations were introduced to reflect major areas of uncertainty when modeling the real world. For instance, when modeling medical decision making, random variations could be used as multipliers between the treatments given to patients and the resulting conditions of the patients. Because there is a level of uncertainty as to the effectiveness of the treatments or the significance of the patient's nature healing process, the use of random variations would be necessary. For this experiment random

variations was incorporated in the form of drift, measurement noise and model noise.

A drift random variate was used to reflect the direction of the environment's progress. For instance, if an individual possessed a certain amount of wealth, the value of his wealth would be affected by the inflation or deflation rate regardless of his investment decision. Inflation and deflation rates reflect the direction of the economy, and are considered as drift variates.

A measurement random variate was used to adjust individual factors to reflect the imprecision in decision process measurements. A model random variate was used to adjust aggregates to reflect the imprecision in decision environment measurements. Consider, for example, constructing a model to define the gross national product (GNP) at any time. There are many inaccuracies associated with measuring factors such as consumption, governmental expenditures, and gross investment for an entire nation. Measurement random variates should be used to represent these inaccuracies. Secondly, the concept of GNP, itself is ambiguous and based on many different conventions which is suggestive by the various methods use to determine it. Model random variates would be appropriate to reflect the obscurity associated with GNP.

Feedback is information about the gap between the actual level and the reference level of a system parameter

that is used to affect the gap. For example, information on the overbudgeting on contracts by a contracting agent used to cut his obligations in the future is feedback. The system parameter is the contracting agent's expenditures. The reference level is the budgeted expenditures; the actual level is the actual expenditures. Information on how to affect the gap is feedback (Ramaprasad, 1983).

Feedback provides information about the outcome of prior actions, changes to the environment, and changes as a result of the decision maker's previous decisions. This information is essential in human information processing to help develop mechanisms for dealing with the environment. Feedback can be used as an effective tool to enhance the quality of decisions.

The factors associated with feedback are the type of feedback, feedback delay and feedback quality. There are various types of feedback strategies (i.e., outcome feedback, cognitive feedback, and feedforward), however, this experiment was design to utilize outcome feedback only.

Feedback delays are the periods of time between when the action takes place and when information about the effects of that action arrives. In complex systems, feedback delays are inevitable and may occur anywhere in the feedback loop. For example, during Operation Desert Storm when air strikes were flown over Iraq, there was a significant feedback delay between the time when the bombs

were dropped and when the status of the target was determined. In many cases, secondary missions against the same target were flown without knowing the results of the first attack.

The second factor is the quality of feedback. In dynamic task, all information is feedback information, but the information may vary in quality and frequency. In our example above, various sources were utilized to verify the status of the target (i.e., CNN, observation aircraft, satellite imaginary, etc.). However, there are varying degrees in the quality of information provided by each of these source. An observer on the ground may provide more detailed information than an aerial photography from an observation aircraft.

The relation between the decision environment (characteristics of the processes to be controlled) and the decision process of the individual (those of the processes used for control) defines the strategy for the task. For example, an investor may develop a strategy for investing his money. If he does not have the time, resources or know how to adequately track the stock market, he may chose a time valued strategy, where he would invest regularly regardless of the fluctuations in the market. In this experiment, strategies are implemented through the use of decision rules.

C. RESEARCH QUESTION

Research conducted in behavioral decision theory studies has identified heuristics used by people in a variety of decision making areas. However, this research has been primarily centered on individual choice in static and discrete incidents. Hogarth (1981) emphasized that "judgment is part of an interactive process that people use to cope with the environment" and that "a discrete-continuous perspective is necessary in evaluating judgmental heuristics."

Sterman (1989a) contends that experimental studies of the "continuous, adaptive nature of judgmental processes" in a dynamic system can be performed in the laboratory with computer simulation models. Simulation modeling can represent the complexity of the environment and the institutional structure allowing for controlled manipulation and accuracy.

The research outlined in this thesis was conducted to examine the quality of decisions made by individuals in dynamic decision environments and how the quality of decisions in such environments can be improved through decision support tools. Individual behavior was simulated through a set of decision rules. These decision rules varied in levels of complexity from simple to complex. Some of the decision rules utilized feedback oriented strategies, while others incorporated a learning mechanism. Each of the

decision rules interacted through computer simulation with 120 different environments.

D. CONTRIBUTION

The use of computer simulation modeling has long been recognized as a viable means of representing complex, multifacet environments for studying human behavior. But until recently, dynamic decision studies had not received the attention they merit. Presently, progress in this area is slow because;

1. of the difficulty extending experimental methods used to study individual decisions to aggregate dynamic settings,
2. the decision problems do not fit the mold for normative theory, and
3. analytical solutions are difficult to find.

The goal of this research is to assist in developing formal decision rules that aquate to human behavior, provide a means of exploring alternative assumptions in modeling, and provide strong prediction about human performance that may lead to testable theories.

II. THEORETICAL PREMISE

A. DYNAMIC DECISION MAKING

The descriptive characteristics of a dynamic decision problem are that (Brehmer, 1987):

1. it requires a series of decisions aimed at reaching a specific goal,
2. the decisions are interdependent,
3. the environment changes both, spontaneously and as a result of the decision maker's actions, and
4. the decisions are made in real time.

An example of a dynamic task, would be an F-15 pilot engaged in air to air conflict. The pilot must make a series of decisions aimed at destroying the enemy target. Each decision he makes will affect his next decision. If he chooses to descend to a certain attitude, then he may restrict his maneuver option in the next decision. The situation changes, both as a result of his decisions and as a result of the enemies actions. The enemy aircraft may choose to take an attack posture or flee. The decisions that the pilot makes are in real time.

This means that decision makers must be able to consider the impact of each decision on future decisions, recognize the constraints created by previous decisions (Brehmer, 1987) and realize the ability to correct problems

created by previous decisions in latter decisions (Hogarth 1981).

The real-time character of dynamic decisions requires the decision maker to response quickly to the demands of the environment. This places an element of stress on the decision maker to exert control over the rate at which decision have to be made and to devise a strategy for making good decisions (Brehmer, 1987). In essence, the decision maker must find "a way to use one process to control another process" (Brehmer and Allard, 1991a).

B. STATIC VS DYNAMIC DECISION ENVIRONMENTS

When examining human judgmental ability, it is necessary to distinguish between static and dynamic decision environments. Much of the research conducted in behavioral decision theory on decision making consists of discrete occurrences taking place in a seemingly static environment. Nevertheless, these occurrences are a subset of, and serve to accentuate, continuous processes in a dynamic environment. Since most decisions are made in a dynamic as opposed to static environment, it is argued that biases noted in discrete occurrences result from heuristics that are useful in more natural continuous environments. According to Hogarth (1981) failure to study and evaluate judgment as a continuous process has had two notable pitfalls:

First, insufficient attention has been paid to the effects of feedback between organism and environment. Second, although judgmental performance has been evaluated according to the principles of optimal behavior implied by decision theory and the probability calculus, few researchers have questioned whether the assumptions of such models apply to continuous processes. (p.198)

C. HOW DYNAMIC DECISION MAKING CAN BE STUDIED

The study of dynamic task provides unique challenges in that standard normative theories for decisions making do not apply (Brehmer, 1987) and optimal solution are impossible to obtain through analytical means (Sterman, 1989b). For these reasons, studies of dynamic decision making have largely abandoned the normative approach and concentrated on empirical analysis. A general framework for studying dynamic decision making was adopted to guide research.

Brehmer (1987) pointed out (as denoted by Broadbent, Fitzgerald and Broadbent (1986), Rapoport (1975) and Mackinnon and Wearing (1985) earlier) that the goal of decision making is to achieve control and that decisions are made to achieve a desired state of affairs, or keep a system at a desired state. From this observation, it was suggested that control theory would be a viable approach to studying dynamic decision making. It was later determined that the control theory approach was inappropriate because of its inability to handle patterns and gestalts (Bainbridge, 1981).

However, control theory was productive in that it defined both the conditions for the system and the

properties of the decision maker, necessary to control the system. Conditions for the system are that it must be possible to ascertain and affect the state of the system. Properties of the decision maker are that there must be a goal and a model of the system. The problem for research is concerned with the properties of the decision maker as a function of the conditions of the system being controlled (Brehmer, 1987). This task is not as simple as it might appear. Conditions of the system are abstract and it is unclear as to what determines and affects the state of the system. The second problem involves adopting a correct strategy (i.e., feedback, feedforward or some combination thereof).

Because of the complexity of most dynamic systems, traditional methods of field studies are not feasible. Computers have made it possible to create dynamic simulations (commonly called "microworlds") and to study how subjects interact with such complex environments.

In microworld experiments the decision problems are not controlled by experimenter, but by the behavior of the decision maker. The state of the system at any given moment is reliant on both the system's characteristics and the decision maker's decisions. Since the independent variables of the experiment are the system's characteristics, the decision maker's strategies must be the area of focus.

The experimental approach was used to examine our research questions. In this approach, subjects' performance in simulations with varying characteristics are compared.

D. IMPORTANCE OF FEEDBACK IN DYNAMIC DECISION ENVIRONMENTS

Hogarth (1981) laments the "insufficient attention" paid "to the effects of feedback between organism and environment." Feedback, not only refers to outcome feedback, but also encompasses environmental changes, and changes as a result of the decision maker's previous decisions. Essentially all human judgment is used to facilitate action which induce feedback that is central to human judgmental ability to cope with the environment.

These events create a judgment-action-outcome feedback loop. The feedback is often immediately available, however, feedback delays are indicative of most dynamic systems.

Hogarth (1981) suggests that the very "ubiquity" of feedback has caused its importance as a part of this loop to go unnoticed. As Powers (1973) stated:

All behavior involves strong feedback effects, whether one is considering spinal reflexes or self-actualization. Feedback is such an all-pervasive and fundamental aspect of behavior that it is as invisible as the air we breathe. Quite literally it is behavior--we know nothing of our own behavior but the feedback effects of our own outputs. (p. 351)

1. Judgmental Accuracy

Different degrees of judgmental accuracy are required in discrete and continuous processes. Imagine

predicting future sales in an organization. Choice is represented by the selection of a target sales quantity. Consider the probability of reaching that sales quantity, randomly, without having any means to predict the behavior of the market. Provided that sales are being made, the probability of reaching the target sales quantity in a discrete incident is an increasing ratio of the target sales quantity to the distance from the target sales quantity. Starting from the same point, a continuous process, by moving toward the target sales quantity and periodically checking the quantity of sales, could transform a low initial probability to almost certainty without exercising much predictive abilities. For a continuous process, the probability of accurately predicting some economic variable increases as a function of time. This example highlights two critical dimensions of judgmental achievement: (a) the implied degree of commitment and (b) that the availability and interpretation of feedback is more important than predictive ability (Hogarth, 1981).

2. Commitment

Feedback is essential to human judgmental ability to make adaptive responses by reducing the implied commitment. Outcome feedback provides information about the response, whereas process feedback provides information concerned with the relations that create those responses. Outcome and process feedback are products of discrete

incidents research. In continuous processes, feedback is more corrective in nature, in that it allows for changes in the general direction of judgment (Hogarth, 1981). Problems created by earlier decisions can be corrected during latter decisions. Corrective feedback gives the illusion of a planned complex series of behavior being performed by the decision maker when actually they are simple actions performed across time (Hogarth, 1981). This incrementally approach greatly reduces the level of commitment implied by a specific action as compared to level of commitment obtain from complex calculations with a more discrete approach. In continuous processes, conditions involving feedback greatly influences task complexity. Frequency and speed of corrective actions are therefore, important variables when characterizing judgmental task (Powers, 1978).

E. HYPOTHESIS

Two primary hypothesis guide the research questions. The first primary hypothesis addresses learning in decision processes. This is accomplished by comparing performance measures of decision processes to those of decision processes that incorporate learning in corresponding decision environments. We would expect decision processes with learning to perform better than those without when operating in the same environment. The first hypothesis is therefore:

Decision processes that incorporate learning would out perform other decision processes interacting in similar environments.

The second hypothesis is concerned with system characteristics that affect decision processes. This is accomplished by measuring the performance of each decision process in each decision environment. Each decision environment have varying degrees of complexity (details on the constructs the decision environments provided in Chapter III). We would expect that decision processes would perform better when operating in a less complex environment. This leads us to the second hypothesis:

Decision processes interacting in simple environments would out perform the same processes in complex environments.

III. METHOD

A. TASK ENVIRONMENT

1. Dynamic Decision Task

The decision environment used here did not take on a specific application, but contains the general structure that encompass many other decision environments. The basic task is to analyze the system, use the cues to make inferences to the system's condition and then select the appropriate strategy. The goal of the task is to take an initial amount and maximize its value through various decision strategies.

2. Decision Environment

Three levels of complexity were tested. These were the number of elements, the relations between elements and random variations. The number of elements comprised models of 5 and 10 variables. Relations between elements were split into two factors; causal structure and time lags. The causal structure refers to the type of feedback structure. The causal structure in the models are classified as positive, negative, or mixed. The time lag indicates the elapsed time between when an action occurs and when the feedback from that action is observed. Time lags in the models are classified as high or low. High indicates that feedback is available for 50% or less of the observed

periods at the time of the present judgment. This criterion indicates that there is a long lag time between when the decision is made and when feedback from that decision is available. Low time lags mean that feedback is available for more than 50% of the observed periods at the time of the present judgment. This includes the case when feedback is immediately available.

Random variation was separated into three factors; drift, measurement noise, and model noise. It was initiated from a large randomly generated table (110 columns X 10,000 rows). The values for the table was produced from a random number generator with a seed of 48. Columns 0-99 were allocated for measurement variate and columns 100-109 for model variate. The random values in the table was scaled to a specific range between 1 and -1 to moderate their impact.

An upward drift was assigned an arbitrary value of 0.5, a downward drift -0.5 and no drift 0. The drift value, manipulated algebraically with the contents of the randomly generate table, disseminated the effect of the drift throughout the experiment. Drift was operationalized with the following equation, embedded within two iterative structures which manipulated the table:

```
random[i][j]=random[i][j]+(i*drift)/MAX_PERIODS
```

Measurement variate was added to each element at the time of processing. Model variate was added to the aggregates during processing to introduce uncertainty.

TABLE 1. STRUCTURE OF MODELS OF THE DECISION ENVIRONMENT

<u>number of elements</u>	<u>environment</u>	<u>casual structure</u>	<u>time lag</u>
5	simple	negative	low
		positive	high
		mixed	
5	complex	negative	low
		positive	high
		mixed	
10	simple	negative	low
		positive	high
		mixed	
10	complex	negative	low
		positive	high
		mixed	

Five models of each of the combinations in Table 1. were constructed producing a total of 120 models of the decision environment. Five models of each were chosen to provide validity and to reinforce observed results. Mathematical representations of the models are contained in the Appendix.

The models of the decision environment were constructed utilizing random generators. Random values for the variable coefficients were produced and scaled, so that the sum of the coefficients would be equal to 1. Negative signs were assigned to the coefficients to indicate negative casual structures. Mixed causal structures were formed by assigning negative signs at random. For low lag times, the criteria was set for lag times lower than 50% of the observed periods. For high lag times, the criteria was set

for lag times greater than or equal to 50% of the observed periods. For the interconnections, the variables were randomly generated within a range from 0 to the number of elements.

3. Decision Strategies

Decision strategy for a task is defined by the relations between the decision environment and the decision processes used to control that environment. These decision strategies are implemented through the use of decision rules. Hogarth (1981) speculates that simple decision rules which are known to be within human cognitive abilities can perform as well as complex rules. Studies have shown that for series that do not conform to known model of their characteristics change, simpler models provide more accurate forecast (Makridakis and Hibon, 1979). For these reasons, the following simple strategies for weighted moving averages, moving averages, random arbitrary strategy, constant arbitrary strategy and no action strategy were adopted.

A strategy for weighted moving averages involves differentially weighing the averages of the observed periods with emphasizes on the most recent observation. The weighing distribution, assigns 50% of the weight to the most recent observation and smaller weights as the period of observation become more distant from the most recent decision. The present decision D is determined by applying

a weighing distribution WGT to the wealth WL for the previous observed periods OP and is given by:

$$D = (WGT)WL_{t,1} + (WGT - (1/OPX2))WL_{t,2} + (WGT - (2/OPX2))WL_{t,3} + \dots$$

where $WGT = (0.5 \times OP) / (OPX2)$

This a feedback oriented strategy that takes into account the information provided from previous decisions.

A strategy for moving averages involves taking the average of the observed periods as judgment for the present decision. The present decision D is determined by averaging the wealth WL from the previous observed periods OP and is given by:

$$D = WL_{t,1} + WL_{t,2} + WL_{t,3} + \dots$$

This also a feedback oriented strategy that utilizes the results of previous actions to determine the present decision. The feedback from the all of the observed periods are considered of equal value.

A random arbitrary strategy involves randomly selecting a value as judgment for the present decision. This is accomplished in this model by taking a percentage of the incremental value of the most recent observation as judgment for the present decision. This strategy is non-feedback oriented and can be considered as a form of trial-and-error rather than optimizing (Hogarth and Makridakis, 1981).

A constant arbitrary strategy involves using a predetermined value as judgment for the present decision. This strategy is similar to that of the random arbitrary

strategy. The only different is that, the value remain constant throughout the experiment. This approach can be compared to the time investment strategies use by investor where they invest a constant amount regularly regardless of the fluctuations of the market. This strategy is not affect by feedback and usually has a high level of commitment associated with it (Hogarth and Makridakis, 1981).

A no action or do nothing strategy involves taking no action. Although, this may appear to be a easy decision, there are visible penalties associated with this type of a strategy (i.e., value changes as a result of environmental drift). The decision to take no action may still involve a significant level of evaluating alternatives although no action is taken (Hogarth and Makridakis, 1981).

In addition to the above strategies, a multiple regression algorithm was used to incorporate learning. A learning system has two goals; to deal with complex real-world decision making and to provide correct solutions. Decision makers are constantly faced with making important decisions and in doing so they rely on prior experience. Learning systems make decisions based on accumulated experience contained in successfully solved cases (Weiss and Kulikowski, 1990).

The multiple regression algorithm utilizes cues from observed periods to make inferences as to the condition of the environment. Averages of these cues are then used to

produce beta values to determine the weighing distribution of the cues in the present decision. The sum of weighing distribution across elements was set equal to 1. This strategy determines the importance of each of the cues in previous decisions, thereby allowing for strong emphasis to be placed on the cues relative to the present decision.

4. Dependent Measures

The performance of each decision strategy was operationalized through two dependent measures: the mean wealth (WLMEAN), and the mean accumulated wealth (ENDWL). The mean wealth is the mean of the incremental changes between periods or iterations. The mean accumulated wealth or ending wealth is the mean of the aggregate sum of the incremental changes.

Two additional dependent variables were used in the analysis process to determine the statistical significance of system parameters: the standard deviation of wealth (WLSTD), and the mean periods (PERIODS). The standard deviation of wealth is self explanatory. The mean periods is the mean of the number of periods or iterations that the experiment successfully completed prior to terminating. The affects of all four dependent variables in the analysis process are presented in terms of probabilities (P) and F statistical values.

E. CONDUCT OF THE EXPERIMENT

The initial conditions of the experiment were set as follows:

1. number of iterations 1000
2. initial value 10
3. noise present
4. maximum input value for random variations 10
5. minimum input value for random variations -10
6. threshold value -1000
7. no model changes
8. drift variate -0.5

The number of iterations determined how long the simulation would run under ideal conditions. The number of iterations remained constant throughout the experiment. Data on shorter iteration periods could be derived from the output produced. The initial value indicated the starting value for the aggregate total and was used only at the beginning of each simulation. The two input values used in an algebraic equation specified the range for the random variations. The range was set for values between 1 and -1 throughout the experiment. The threshold value or endpoint determined the condition at which the simulation model would terminate. If the accumulated wealth moved below the endpoint value the simulation would end. The endpoint value remained constant throughout the experiment. Data on larger threshold values could be derived from the output produced.

A single decision model was observed during each simulation, therefore, no model changes were indicated. Decision models were arranged in groups of five based on the factors discussed in section 3. Of the five model series, a negative drift variate (-0.5) was used in combination with the first two decision models, no drift variate with the third model, and a positive drift variate (0.5) with the last two models of the series.

IV. RESULTS

A. EXPERIMENTAL RESULTS

Even the limited group of task variables and decision strategies described in Chapter III allow for a large number of simulation experiments. In this study, a factorial design was used for evaluating the six alternative strategies. The experiments were conducted to detect specific interactions among task variables as well as task variable-by-strategy interaction. A two stage approach to designing the experiment was used. The first stage consisted of comparison of six strategies across factorial manipulation of the task parameters. The second stage consisted of comparison of decision strategies across the manipulations of single and combined task parameters.

The first analysis compared the six different decision strategies across manipulations of four parameter: (1) number of elements, (2) complexity, (3) causal structure, and (4) time lag. The expected results would be for all of the decision strategies' performance to improve as the number of elements and complexity increase, while increased time lag should have a negative impact. The results of the experiment are summarized in Tables 2 and 3 based on the mean value of wealth and accumulated wealth.

TABLE 2. MEAN VALUE OF WEALTH

NE	C	CS	TL	Strategies					
				A	K	M	N	R	W
5	simple	neg	low	-1.32	-2.26	-0.52	-0.55	-0.34	-0.82
			hi	-1.35	-2.29	-0.52	-0.51	-0.31	-0.83
		pos	low	-2.13	-2.71	-1.18	-0.52	-1.36	-1.67
			hi	-2.30	-2.95	-1.26	-0.72	-1.35	-1.80
	complex	mix	low	-1.64	-2.61	-0.65	-0.62	-0.33	-1.04
			hi	-1.82	-2.63	-0.78	-0.33	-0.68	-1.25
		neg	low	-1.38	-2.33	-0.49	-0.54	-0.09	-0.81
			hi	-1.30	-2.28	-0.47	-0.55	-0.06	-0.76
10	simple	pos	low	-3.00	-3.42	-1.84	0.10	-2.67	-2.52
			hi	-2.44	-3.04	-1.54	1.12	-1.70	-2.01
		mix	low	-1.64	-2.57	-0.66	-0.57	-0.56	-1.07
			hi	-1.67	-2.44	-0.75	-0.26	-0.54	-1.15
	complex	neg	low	-2.07	-2.96	-0.85	-0.32	0.26	-1.38
			hi	-2.05	-2.84	-0.92	-0.56	0.10	-1.44
		pos	low	-4.47	-4.95	-2.53	-1.15	-2.53	-3.67
			hi	-3.92	-4.33	-2.24	-0.84	-2.07	-3.21
10	simple	mix	low	-2.37	-3.33	-0.97	-0.30	0.18	-1.61
			hi	-2.37	-3.17	-1.08	-0.61	-0.14	-1.69
		neg	low	-1.85	-2.57	-0.72	-0.59	0.74	-1.15
			hi	-1.72	-2.60	-0.80	-0.60	0.42	-1.27
	complex	pos	low	-4.22	-7.50	-5.30	2.68	-6.95	-6.54
			hi	-4.36	-4.83	-3.13	0.79	-3.59	-3.88
		mix	low	-2.00	-2.89	-0.85	-0.61	0.62	-1.35
			hi	-2.26	-3.00	-1.02	-1.01	0.02	-1.61

KEY:

NE = Number of Elements
 C = Complexity
 CS = Causal Structure
 TL = Time Lag

STRATEGIES:

A = Random Arbitrary
 K = Constant Arbitrary
 M = Moving Average
 N = Do Nothing
 R = Regression
 W = Weighted Moving Average

TABLE 3. MEAN VALUE OF ACCUMULATED WEALTH**Strategies**

NE	C	CS	TL	A	K	M	N	R	W
5	simple	neg	low	-420.59	-473.06	-257.62	-261.52	-160.83	-382.14
			hi	-419.39	-455.77	-262.11	-254.60	-151.75	-377.38
		pos	low	-391.01	-423.23	-392.22	-189.57	-454.37	-384.89
			hi	-373.00	-420.72	-376.27	-265.87	-365.56	-183.30
		mix	low	-412.54	-462.26	-310.26	-294.02	-165.28	-384.44
			hi	-397.48	-435.28	-358.56	-103.84	-270.41	-387.32
	5 complex	neg	low	-412.82	-441.56	-244.66	-270.88	-47.24	-388.38
			hi	-422.05	-457.05	-238.53	-274.36	-13.42	-378.69
		pos	low	-351.50	-345.95	-374.20	313.90	-460.71	-358.38
			hi	-364.14	-424.65	-352.84	416.07	-336.98	-344.37
		mix	low	-417.99	-470.50	-319.70	-171.55	-272.10	-396.27
			hi	-401.98	-434.26	-327.05	-48.31	-192.97	-382.17
10	simple	neg	low	-409.20	-458.82	-393.34	-143.65	148.00	-381.39
			hi	-398.30	-439.16	-389.39	-261.35	59.76	-373.80
		pos	low	-344.60	-371.42	-359.77	-279.20	-414.26	-331.58
			hi	-317.81	-355.98	-339.00	-175.05	-317.13	-304.29
		mix	low	-401.16	-439.39	-388.84	-72.90	75.04	-378.15
			hi	-389.77	-423.52	-384.61	-122.65	-22.01	-368.88
	10 complex	neg	low	-415.73	-464.27	-339.70	-245.89	397.14	-380.91
			hi	-396.75	-434.39	-368.58	-279.51	210.53	-375.76
		pos	low	-334.31	-274.71	-281.16	1239.89	-310.51	-255.09
			hi	-267.53	-302.67	-274.73	456.89	-232.74	-255.29
		mix	low	-415.93	-455.21	-368.35	-263.23	317.53	-378.77
			hi	-383.42	-414.30	-370.36	-229.48	9.38	-370.46

KEY:

NE = Number of Elements
 C = Complexity
 CS = Causal Structure
 TL = Time Lag

STRATEGIES:

A = Random Arbitrary
 K = Constant Arbitrary
 M = Moving Average
 N = Do Nothing
 R = Regression
 W = Weighted Moving Average

Direct interpretation of the proportion of observed periods should be done in light of the fact the proportion based upon 50 observations for high time lags and 30 observations for low time lags are subject to considerable sampling variability. Differences of more than 0.39 between decision strategies are considered as statistically significant.

Not surprisingly, the regression strategy outperformed many of the other strategies. However, what is surprising, is the performance of the do nothing strategy. In tasks where the causal structure is positive, the do nothing strategy outperforms all others including regression. The best performance of all tasks occurred under the do nothing strategy with parameter of 10 elements, complex environment, positive causal structure, and a low time lag. The regression strategy performed well with parameters of 10 elements, and a negative or mixed causal structure. When comparing the two arbitrary strategies, the random strategy performed slightly better than the constant strategy under all conditions. When comparing the two moving average strategies, the moving average performed slightly better than the weighted moving average under all conditions. Within all strategies, except the do nothing strategy, tasks with a positive causal structure performed worst than all other.

TABLE 4. MAIN EFFECTS AND INTERACTIONS OF COMBINED STRATEGIES

Effects	WLMEAN		WLSTD		PERIODS		ENDWL	
	P	F	P	F	P	F	P	F
C	0.2582	1.28	0.0001	27.77	0.4749	0.51	0.0475	3.94
CS	0.0001	76.99	0.0001	158.18	0.0001	100.45	0.6142	0.49
TL	0.1796	1.80	0.1676	1.91	0.6193	0.25	0.4397	0.60
NE	0.0001	39.13	0.0001	337.16	0.0001	36.68	0.5393	0.38
S	0.0001	57.12	0.0001	69.30	0.0001	79.14	0.0001	23.92
CxNE	0.0154	4.20	0.0001	21.22	0.0431	3.16	0.0121	4.44
CxCS	0.5171	0.42	0.0036	8.52	0.3059	1.05	0.9944	0.00

KEY: C = Complexity
 CS = Causal Structure
 TL = Time Lag
 NE = Number of Elements

WLMEAN = Mean value wealth
 WLSTD = Standard deviation
 ENDWL = Ending Wealth

Tables 4-10 present the results of an analysis of variance. The tables show in bold print those parameters that are statistically significant ($p<0.05$) within each decision strategy across four dependent variables: (1) mean wealth, (2) standard deviation, (3) mean periods, and (4) ending wealth.

Table 4 depicts an overall analysis containing all decision strategies. The causal structure, number of elements, and decision strategy have a strong emphasis on the mean wealth. The significance of the complexity-number of elements can be attributed to the effects of the number of elements.

The wealth standard deviation is strongly influenced by the complexity, causal structure, number of elements, decision strategy, and the complexity-number of elements. To a lesser degree, the complexity-causal structure is significant.

The mean periods is effected by the causal structure, number of elements, decision strategy and, to a lesser degree, the complexity-number of elements.

The mean ending wealth is strongly influenced by the decision strategy and, to a lesser degree, the complexity. The effects of the complexity-number of elements can be attributed to the emphasis on complexity. The effect of the complexity-strategy is a combination of the emphasis on both parameters.

As revealed in the earlier comparison, there is a strong emphasis across all variables on the decision strategy used. Causal structure and the number of elements are equally significant. However, time lag nor complexity plays an essential role in overall performance. The effects of the complexity-number of elements can be attributed to the significance of the number of elements.

Table 5 presents the results for the learning strategy using regression. The causal structure and complexity have strong emphasis on the mean wealth. The emphasis of the complexity-causal structure can be attributed to the affects of the individual parameters.

The wealth standard deviation and mean periods are strongly influenced by the causal structure, number of elements, and the complexity-causal structure. Complexity is also significant, to a lesser degree. The mean ending wealth is significantly influenced by the causal structure and the number of elements.

There is a strong emphasis on causal structure across all four dependent variables. The number of elements and, to a lesser degree, complexity is emphasized across three of the four dependent variables. The emphasis on the complexity-causal structure can be attributed to both parameters.

Table 6 presents the results for the do nothing strategy. The complexity and the complexity-causal structure have a strong emphasis on the mean wealth. The wealth standard deviation is strongly influenced by the complexity, causal structure, and the number of elements. The mean periods is effected by the causal structure. The mean ending wealth is strongly influenced by the complexity, causal structure and the combination of the two.

There is a primary emphasis on causal structure, complexity, and, to a lesser degree, the number of elements across two of the four dependent variables.

Table 7 presents the results for the weighted moving average strategy. The mean wealth is strongly influenced by the causal structure and the number of elements. The wealth

TABLE 5. MAIN EFFECTS AND INTERACTIONS OF
LEARNING STRATEGY USING REGRESSION

Effects	WLMEAN		WLSTD		PERIODS		ENDWL	
	P	F	P	F	P	F	P	F
C	0.0241	5.23	0.0422	4.23	0.0424	4.22	0.0623	3.55
CS	0.0001	74.84	0.0001	81.27	0.0001	75.35	0.0001	63.89
TL	0.2218	1.51	0.2939	1.11	0.5830	0.30	0.4233	0.65
NE	0.2449	1.37	0.0001	56.60	0.0108	6.73	0.0001	28.98
CxCS	0.0001	11.31	0.0006	7.91	0.0114	4.66	0.1670	1.82
CxTL	0.1384	2.23	0.1996	1.67	0.6144	0.26	0.9804	0.00
CxNE	0.1972	1.68	0.2151	1.55	0.6992	0.15	0.2782	1.19

KEY:
 C = Complexity
 CS = Causal Structure
 TL = Time Lag
 NE = Number of Elements

WLMEAN = Mean value wealth
 WLSTD = Standard deviation
 ENDWL = Ending Wealth

TABLE 6. MAIN EFFECTS AND INTERACTIONS OF
DO NOTHING STRATEGY

Effects	WLMEAN		WLSTD		PERIODS		ENDWL	
	P	F	P	F	P	F	P	F
F								
C	0.0433	4.18	0.0103	6.82	0.6397	0.22	0.0112	6.66
CS	0.0646	2.81	0.0021	6.51	0.0015	6.93	0.0014	6.94
TL	0.7541	0.10	0.5682	0.33	0.3366	0.93	0.9324	0.01
NE	0.8105	0.06	0.0001	38.12	0.5007	0.46	0.6066	0.27
CxCS	0.0032	6.04	0.2831	1.28	0.7918	0.23	0.0005	8.26
CxTL	0.7964	0.07	0.5026	0.45	0.7117	0.14	0.8638	0.03

KEY:
 C = Complexity
 CS = Causal Structure
 TL = Time Lag
 NE = Number of Elements

WLMEAN = Mean value wealth
 WLSTD = Standard deviation
 ENDWL = Ending Wealth

standard deviation is strongly effected by all parameters except for the time lag, and the complexity-time lag. The mean period is strongly influenced by the causal structure and the number of elements.

There is a strong emphasis on causal structure and the number of elements across mean wealth, mean standard deviation and mean periods. Complexity is significant for a single dependent variables. The emphasis on the complexity-causal structure is a result of the effects of the causal structure. There is very little difference in the parameters emphasized in the weighted moving average and the moving average strategies (Table 8). In both cases, all parameters are insignificant when determining the mean ending wealth.

Table 9 presents the results from the constant arbitrary strategy. The mean wealth is strongly influenced by the causal structure and the number of elements. The wealth standard deviation is strongly effected by the complexity, causal structure, number of elements, and the complexity-causal structure. The parameters are insignificant when determining the mean periods. The mean ending wealth is strongly influenced by the causal structure.

There is a strong emphasis on causal structure and the number of elements across mean wealth and wealth standard deviation. A single dependent variable emphasis on

TABLE 7. EFFECTS AND INTERACTIONS OF
WEIGHTED MOVING AVERAGE STRATEGY

Effects	WLMEAN		WLSTD		PERIODS		ENDWL	
	P	F	P	F	P	F	P	F
C	0.2258	1.48	0.0025	9.56	0.6638	0.19	0.3801	0.78
CS	0.0001	26.95	0.0001	28.45	0.0001	30.75	0.4501	0.80
TL	0.3730	0.80	0.1925	1.72	0.6386	0.22	0.3933	0.73
NE	0.0001	18.43	0.0001	81.75	0.0001	23.37	0.3391	0.92
CxCS	0.0674	2.76	0.0016	6.84	0.3337	1.11	0.4697	0.76
CxTL	0.3611	0.84	0.1535	2.07	0.8963	0.02	0.3943	0.73
CxNE	0.5336	0.39	0.0216	5.43	0.5679	0.33	0.3811	0.77

KEY: C = Complexity

WLMEAN = Mean value wealth

CS = Causal Structure

WLSTD = Standard deviation

TL = Time Lag

ENDWL = Ending Wealth

NE = Number of Elements

TABLE 8. MAIN EFFECTS AND INTERACTIONS OF
MOVING AVERAGE STRATEGY

Effects	WLMEAN		WLSTD		PERIODS		ENDWL	
	P	F	P	F	P	F	P	F
C	0.0855	3.01	0.0013	10.88	0.4279	0.63	0.6994	0.15
CS	0.0001	30.98	0.0001	19.16	0.0001	67.20	0.1686	1.81
TL	0.3853	0.76	0.1461	2.14	0.7260	0.12	0.8423	0.04
NE	0.0001	17.33	0.0001	105.46	0.0001	16.62	0.0761	3.21
CxCS	0.0158	4.31	0.0036	5.93	0.1229	2.14	0.9504	0.05
CxTL	0.3427	0.91	0.2142	1.56	0.6796	0.17	0.9880	0.00
CxNE	0.3129	1.03	0.0110	6.69	0.5998	0.28	0.9198	0.01

KEY: C = Complexity

WLMEAN = Mean value wealth

CS = Causal Structure

WLSTD = Standard deviation

TL = Time Lag

ENDWL = Ending Wealth

NE = Number of Elements

complexity and the complexity-causal structure.

Table 10 presents the results of the random arbitrary strategy. The mean wealth is strongly influenced by the causal structure and the number of elements. The wealth standard deviation is strongly effected by the causal structure and the number of elements. The mean periods is strongly influenced by the causal structure and number of elements. The system parameters are insignificant when determining mean ending wealth.

There is a strong emphasis on causal structure and the number of elements across mean wealth, wealth standard deviation, and mean periods.

Using a random arbitrary strategy as a baseline for assessing performance, helps to avoid the difficulties of formulating normative models for dynamic tasks (Hogarth, 1980; Hogarth and Makridakis, 1981). Second, the heuristics strategy seems to be within human capabilities, indicating that individuals should be able to obtain comparable results which maybe confirmed through direct experimentation. From a review of the individual strategies, it is apparent that the causal structure and the number of elements plays a very significant part in the strategies' performance. In some instance, complexity was significant, but normally across a single dependent variable. However, it is apparent that time lag was insignificant in determining performance.

TABLE 9. MAIN EFFECTS AND INTERACTIONS OF
CONSTANT ARBITRARY STRATEGY

Effects	WLMEAN		WLSTD		PERIODS		ENDWL	
	P	F	P	F	P	F	P	F
C	0.4844	0.49	0.0322	4.71	0.9621	0.00	0.1330	2.29
CS	0.0001	13.00	0.0001	33.69	0.3864	0.96	0.0293	3.65
TL	0.2884	1.14	0.4277	0.63	0.9094	0.01	0.4063	0.69
NE	0.0002	14.99	0.0001	80.55	0.2266	1.48	0.8870	0.02
CxCS	0.1817	1.73	0.0148	4.38	0.8768	0.13	0.5342	0.63
CxTL	0.4730	0.52	0.1384	2.23	0.8705	0.03	0.7582	0.10
CxNE	0.7336	0.12	0.1047	2.68	0.8834	0.02	0.9648	0.00

KEY:
 C = Complexity
 CS = Causal Structure
 TL = Time Lag
 NE = Number of Elements

WLMEAN = Mean value wealth
 WLSTD = Standard deviation
 ENDWL = Ending Wealth

TABLE 10. MAIN EFFECTS AND INTERACTIONS OF
RANDOM ARBITRARY STRATEGY

Effects	WLMEAN		WLSTD		PERIODS		ENDWL	
	P	F	P	F	P	F	P	F
C	0.9911	0.00	0.1027	2.71	0.6957	0.15	0.8619	0.03
CS	0.0001	16.00	0.0001	26.38	0.0025	6.32	0.9137	0.09
TL	0.9390	0.01	0.7629	0.09	0.7691	0.09	0.9050	0.01
NE	0.0004	13.56	0.0001	74.47	0.0140	6.24	0.7945	0.07
CxCS	0.7266	0.32	0.2202	1.53	0.9596	0.04	0.9822	0.02
CxTL	0.9703	0.00	0.9065	0.01	0.9239	0.01	0.9922	0.00
CxNE	0.5995	0.28	0.3995	0.72	0.5114	0.43	0.9963	0.00

KEY:
 C = Complexity
 CS = Causal Structure
 TL = Time Lag
 NE = Number of Elements

WLMEAN = Mean value wealth
 WLSTD = Standard deviation
 ENDWL = Ending Wealth

The results from the experiment fully supports the first hypothesis that decision processes that incorporate learning would out perform other decision processes interacting in similar environment. The decision strategy that incorporated regression clearly outperform all other strategies in overall performance.

However, the results only partially support the second hypothesis that decision processes interacting in simple environments would out perform the same processes in complex environments. Most of the strategies tend to support this hypothesis in some cases, but there is no clear statistical significance between performance among simple and complex decision strategies.

V. CONCLUSIONS

A. SUMMARY OF RESULTS

The objective of this study was to examine the quality of decisions made by individuals in dynamic decision environments and how the quality of decisions in such environments can be improved through decision support tools. Chapter II (section B) pointed out the pitfalls associated with past research conducted on decision making in discrete instances and emphasized the importance of recognizing decision making as part of a continuous process. Chapter II (section C) discusses the general framework for studying dynamic decision making and introduces computer simulation as a means of studying dynamic tasks.

Chapter II (section D) explains why one would expect a better quality of decisions to be made when examining decision making as a continuous process as opposed to discrete incidents. A key factor to enhancing the quality of decisions, is the role that feedback plays. The results of this study supports this finding. As the analysis of variance test showed, there is a significant difference in the performance of feedback oriented decision strategies as compared to non-feedback oriented decision strategies. The decision strategies which utilized feedback in decision making outperform those that utilized arbitrary strategies.

However, the do nothing strategy was an exception to the forementioned results. The abnormalities occur when the causal structure is positive. This is not surprising. When left uninterrupted, positive feedback loops tend to feed on themselves (Mackinnon and Wearing, 1985). An example of this virtual cycle is the multiplier accelerator effect (Sterman, 1989b).

Secondly, the decision strategy which incorporates learning through the use of regression, outperforms four of the five other decision strategies. The do nothing strategy produced comparative results.

B. SYSTEMS THAT INCORPORATE LEARNING

The results of this study provides several implications for the use of systems that incorporate learning as decision support tool. This study shows that an evaluation of previous decisions, underlining the importance of environmental factors surrounding those decisions, enhances the quality of the decisions made. Because of the limited cognitive capacity of ^O_A decision maker this may be best accomplished through the development of learning systems.

Additionally, this study supports the use of computer simulation modeling as a means of determining conditions under which specific decision strategies perform better than others and evaluating the affects of system parameters.

The implications of these findings for command decision making indicate that, feedback from prior military actions or engagements can play an important role in adapting existing systems to meet military roles in changing environments.

C. LIMITING FACTORS TO GENERALIZABILITY

Because there is an infinitely large number of task environment-decision strategy combinations, empirical simulations alone will not suffice to provide generalizable results. The extent to which this approach provides useful insights into human problem solving is dependent upon how well these simulated tasks resemble features of the real world. The effects of different types of combinations of environments and decision strategies will need to be linked theoretically to the abilities and limitations of the human information-processing system (Hogarth, 1981). Experiments should utilize representative designs within the discrete framework or be supported by direct experimentation.

D. FUTURE RESEARCH

One path for future research is to develop simulation models with user interfaces that allow for interactive gaming such that proposed decision rules can be replaced by actual subjects (i.e. direct experiment (Sterman, 1987)). The subjects are given freedom to make decision as they

wish, utilizing the same structural context and data sets as those proposed for the model to be tested. The direct experiment results could then be compared to the results from the simulation model to evaluate the adequacy of the modeled decision processes. Research in this context will assist in establishing acceptable decision rules when there is no primary data on decision making available, and build confidence in the simulation model.

APPENDIX

DECISION MODELS USED IN THE EXPERIMENT

$$\begin{aligned}
 Y_1 &= 0.09X_{4,t-5} + -0.21X_{4,t-7} + 0.09X_{3,t-10} + 0.44X_{3,t-14} + 0.17X_{2,t-14} \\
 X_2 &= 0.08X_{1,t-13} + -0.24X_{0,t-7} + -0.29X_{3,t-8} + -0.38X_{2,t-1} + 0.00X_{1,t-13} \\
 X_3 &= 0.00X_{2,t-3} + 0.15X_{4,t-7} + 0.18X_{2,t-9} + 0.46X_{3,t-11} + -0.22X_{1,t-13} \\
 X_4 &= 0.11X_{3,t-1} + 0.11X_{2,t-7} + 0.06X_{3,t-6} + 0.07X_{3,t-11} + 0.65X_{0,t-7} \\
 X_5 &= -0.34X_{0,t-3} + 0.03X_{0,t-7} + -0.27X_{0,t-3} + 0.01X_{2,t-11} + -0.35X_{2,t-9}
 \end{aligned}$$

$$\begin{aligned}
 Y_1 &= -0.23X_{3,t-9} + 0.48X_{3,t-12} + -0.23X_{4,t-13} + 0.05X_{2,t-9} + 0.01X_{4,t-3} \\
 X_2 &= 0.08X_{1,t-5} + 0.63X_{2,t-7} + 0.01X_{3,t-5} + -0.23X_{0,t-9} + 0.04X_{3,t-4} \\
 X_3 &= -0.26X_{1,t-2} + 0.06X_{2,t-1} + -0.34X_{0,t-6} + 0.01X_{1,t-8} + -0.33X_{3,t-12} \\
 X_4 &= 0.12X_{4,t-14} + -0.21X_{3,t-4} + 0.02X_{2,t-3} + 0.58X_{2,t-4} + 0.07X_{0,t-11} \\
 X_5 &= -0.39X_{4,t-1} + 0.42X_{3,t-11} + 0.09X_{2,t-10} + 0.04X_{0,t-6} + 0.06X_{4,t-12}
 \end{aligned}$$

$$\begin{aligned}
 Y_1 &= 0.82X_{2,t-12} + 0.06X_{1,t-14} + 0.06X_{3,t-11} + 0.04X_{0,t-14} + 0.03X_{1,t-10} \\
 X_2 &= 0.03X_{4,t-5} + -0.27X_{1,t-15} + -0.37X_{4,t-2} + 0.05X_{1,t-11} + -0.27X_{1,t-1} \\
 X_3 &= -0.21X_{3,t-3} + 0.11X_{0,t-9} + 0.46X_{1,t-1} + 0.18X_{3,t-2} + 0.05X_{0,t-6} \\
 X_4 &= 0.51X_{1,t-3} + 0.00X_{3,t-2} + -0.39X_{2,t-2} + 0.00X_{3,t-3} + 0.09X_{0,t-4} \\
 X_5 &= -0.23X_{1,t-10} + -0.28X_{1,t-9} + 0.01X_{2,t-2} + 0.47X_{4,t-2} + 0.01X_{3,t-1}
 \end{aligned}$$

$$\begin{aligned}
 Y_1 &= -0.45X_{3,t-8} + -0.03X_{3,t-11} + -0.48X_{0,t-6} + 0.02X_{2,t-5} + -0.01X_{3,t-12} \\
 X_2 &= 0.15X_{3,t-5} + 0.15X_{1,t-12} + 0.00X_{4,t-9} + -0.22X_{1,t-1} + 0.49X_{0,t-9} \\
 X_3 &= -0.69X_{1,t-14} + 0.15X_{4,t-7} + 0.02X_{3,t-8} + 0.05X_{2,t-4} + 0.09X_{2,t-7} \\
 X_4 &= 0.00X_{2,t-4} + 0.07X_{4,t-4} + -0.47X_{2,t-5} + -0.01X_{1,t-3} + -0.46X_{2,t-11} \\
 X_5 &= 0.00X_{2,t-3} + -0.26X_{2,t-7} + -0.03X_{0,t-7} + 0.10X_{3,t-8} + 0.61X_{0,t-2}
 \end{aligned}$$

$$\begin{aligned}
 Y_1 &= -0.21X_{1,t-13} + 0.00X_{1,t-11} + -0.26X_{4,t-3} + 0.18X_{1,t-9} + -0.34X_{2,t-13} \\
 X_2 &= -0.38X_{2,t-14} + -0.25X_{1,t-12} + 0.10X_{2,t-5} + -0.27X_{3,t-4} + 0.00X_{1,t-7} \\
 X_3 &= -0.30X_{1,t-4} + 0.00X_{0,t-7} + -0.39X_{1,t-3} + -0.27X_{2,t-13} + 0.03X_{2,t-8} \\
 X_4 &= 0.11X_{1,t-10} + 0.53X_{1,t-4} + -0.29X_{4,t-5} + 0.07X_{1,t-11} + 0.01X_{0,t-10} \\
 X_5 &= -0.24X_{2,t-12} + 0.45X_{2,t-3} + 0.11X_{1,t-7} + 0.14X_{1,t-10} + 0.06X_{2,t-6}
 \end{aligned}$$

$$\begin{aligned}
 Y_1 &= -0.38X_{0,t-7} + -0.01X_{2,t-2} + -0.12X_{2,t-1} + -0.49X_{0,t-6} + -0.00X_{4,t-3} \\
 X_2 &= -0.02X_{4,t-13} + -0.32X_{3,t-11} + -0.02X_{2,t-2} + -0.32X_{3,t-10} + -0.32X_{0,t-3} \\
 X_3 &= -0.17X_{4,t-10} + -0.23X_{0,t-11} + -0.00X_{2,t-5} + -0.42X_{3,t-1} + -0.18X_{4,t-6} \\
 X_4 &= -0.40X_{1,t-6} + -0.13X_{2,t-5} + -0.34X_{2,t-5} + -0.12X_{3,t-4} + -0.01X_{3,t-1} \\
 X_5 &= -0.33X_{3,t-12} + -0.37X_{2,t-7} + -0.27X_{1,t-9} + -0.00X_{0,t-1} + -0.03X_{1,t-9}
 \end{aligned}$$

$$\begin{aligned}
 Y_1 &= -0.11X_{1,t-10} + -0.53X_{1,t-6} + -0.29X_{4,t-5} + -0.07X_{1,t-11} + -0.01X_{0,t-10} \\
 X_2 &= -0.24X_{2,t-12} + -0.45X_{3,t-6} + -0.11X_{1,t-7} + -0.14X_{1,t-10} + -0.06X_{2,t-6} \\
 X_3 &= -0.12X_{4,t-12} + -0.03X_{1,t-11} + -0.41X_{2,t-14} + -0.33X_{1,t-1} + -0.12X_{3,t-5} \\
 X_4 &= -0.01X_{4,t-6} + -0.11X_{3,t-3} + -0.31X_{1,t-8} + -0.25X_{1,t-6} + -0.32X_{4,t-5} \\
 X_5 &= -0.21X_{0,t-13} + -0.17X_{2,t-2} + -0.31X_{2,t-9} + -0.09X_{4,t-14} + -0.22X_{0,t-3}
 \end{aligned}$$

$$\begin{aligned}
Y1 &= 0.39X_{t-6} + -0.04X_{t-8} + -0.25X_{t-13} + -0.31X_{t-5} + -0.00X_{t-4} \\
X2 &= -0.22X_{t-6} + -0.37X_{t-1} + -0.03X_{t-8} + -0.37X_{t-3} + -0.01X_{t-14} \\
X3 &= -0.09X_{t-14} + -0.38X_{t-13} + -0.28X_{t-1} + -0.12X_{t-7} + -0.14X_{t-11} \\
X4 &= -0.67X_{t-1} + -0.02X_{t-7} + -0.15X_{t-10} + -0.13X_{t-4} + -0.03X_{t-13} \\
X5 &= -0.40X_{t-12} + -0.00X_{t-7} + -0.04X_{t-1} + -0.54X_{t-5} + -0.02X_{t-2} \\
\\
Y1 &= -0.20X_{t-14} + -0.59X_{t-3} + -0.14X_{t-4} + -0.06X_{t-14} + -0.01X_{t-2} \\
X2 &= -0.39X_{t-7} + -0.01X_{t-10} + -0.32X_{t-4} + -0.01X_{t-10} + -0.27X_{t-14} \\
X3 &= -0.06X_{t-5} + -0.02X_{t-12} + -0.62X_{t-11} + -0.00X_{t-8} + -0.29X_{t-6} \\
X4 &= -0.06X_{t-3} + -0.00X_{t-6} + -0.29X_{t-12} + -0.06X_{t-3} + -0.59X_{t-4} \\
X5 &= -0.00X_{t-4} + -0.55X_{t-6} + -0.02X_{t-13} + -0.11X_{t-8} + -0.32X_{t-7} \\
\\
Y1 &= -0.08X_{t-4} + -0.21X_{t-3} + -0.29X_{t-8} + -0.30X_{t-12} + -0.12X_{t-9} \\
X2 &= -0.26X_{t-6} + -0.02X_{t-5} + -0.06X_{t-9} + -0.15X_{t-13} + -0.51X_{t-3} \\
X3 &= -0.08X_{t-4} + -0.25X_{t-10} + -0.33X_{t-4} + -0.23X_{t-2} + -0.12X_{t-12} \\
X4 &= -0.35X_{t-3} + -0.29X_{t-1} + -0.09X_{t-14} + -0.16X_{t-7} + -0.11X_{t-3} \\
X5 &= -0.03X_{t-1} + -0.00X_{t-11} + -0.22X_{t-10} + -0.52X_{t-11} + -0.22X_{t-7} \\
\\
Y1 &= 0.09X_{t-5} + 0.21X_{t-7} + 0.09X_{t-10} + 0.44X_{t-14} + 0.17X_{t-14} \\
X2 &= 0.08X_{t-13} + 0.24X_{t-2} + 0.29X_{t-8} + 0.38X_{t-1} + 0.00X_{t-13} \\
X3 &= 0.00X_{t-3} + 0.15X_{t-13} + 0.18X_{t-9} + 0.46X_{t-11} + 0.22X_{t-13} \\
X4 &= 0.11X_{t-1} + 0.11X_{t-13} + 0.06X_{t-6} + 0.07X_{t-11} + 0.65X_{t-7} \\
X5 &= 0.34X_{t-3} + 0.03X_{t-9} + 0.27X_{t-3} + 0.01X_{t-11} + 0.35X_{t-9} \\
\\
Y1 &= 0.23X_{t-9} + 0.48X_{t-12} + 0.23X_{t-13} + 0.05X_{t-4} + 0.01X_{t-3} \\
X2 &= 0.08X_{t-5} + 0.63X_{t-7} + 0.01X_{t-5} + 0.23X_{t-9} + 0.04X_{t-14} \\
X3 &= 0.26X_{t-2} + 0.06X_{t-1} + 0.34X_{t-6} + 0.01X_{t-8} + 0.33X_{t-12} \\
X4 &= 0.12X_{t-14} + 0.21X_{t-4} + 0.02X_{t-1} + 0.58X_{t-4} + 0.07X_{t-11} \\
X5 &= 0.39X_{t-1} + 0.42X_{t-11} + 0.09X_{t-10} + 0.04X_{t-6} + 0.06X_{t-12} \\
\\
Y1 &= 0.82X_{t-12} + 0.06X_{t-14} + 0.06X_{t-11} + 0.04X_{t-14} + 0.03X_{t-10} \\
X2 &= 0.03X_{t-5} + 0.27X_{t-14} + 0.37X_{t-2} + 0.05X_{t-11} + 0.27X_{t-1} \\
X3 &= 0.21X_{t-3} + 0.11X_{t-9} + 0.46X_{t-1} + 0.18X_{t-2} + 0.05X_{t-6} \\
X4 &= 0.51X_{t-3} + 0.00X_{t-2} + 0.39X_{t-2} + 0.00X_{t-3} + 0.09X_{t-4} \\
X5 &= 0.23X_{t-10} + 0.28X_{t-9} + 0.01X_{t-2} + 0.47X_{t-2} + 0.01X_{t-1} \\
\\
Y1 &= 0.45X_{t-8} + 0.03X_{t-11} + 0.48X_{t-6} + 0.02X_{t-5} + 0.01X_{t-12} \\
X2 &= 0.15X_{t-5} + 0.15X_{t-12} + 0.00X_{t-9} + 0.22X_{t-1} + 0.49X_{t-9} \\
X3 &= 0.69X_{t-14} + 0.15X_{t-7} + 0.02X_{t-8} + 0.05X_{t-4} + 0.09X_{t-7} \\
X4 &= 0.00X_{t-4} + 0.07X_{t-4} + 0.47X_{t-5} + 0.01X_{t-3} + 0.46X_{t-11} \\
X5 &= 0.00X_{t-3} + 0.26X_{t-7} + 0.03X_{t-7} + 0.10X_{t-8} + 0.61X_{t-2} \\
\\
Y1 &= 0.32X_{t-4} + 0.33X_{t-10} + 0.01X_{t-10} + 0.28X_{t-1} + 0.06X_{t-10} \\
X2 &= 0.05X_{t-7} + 0.49X_{t-8} + 0.00X_{t-5} + 0.00X_{t-7} + 0.46X_{t-6} \\
X3 &= 0.21X_{t-13} + 0.00X_{t-3} + 0.26X_{t-3} + 0.18X_{t-9} + 0.34X_{t-13} \\
X4 &= 0.38X_{t-14} + 0.25X_{t-3} + 0.10X_{t-5} + 0.27X_{t-4} + 0.00X_{t-7} \\
X5 &= 0.30X_{t-4} + 0.00X_{t-13} + 0.39X_{t-3} + 0.27X_{t-13} + 0.03X_{t-8} \\
\\
Y1 &= -0.23X_{t-42} + -0.25X_{t-35} + 0.07X_{t-41} + -0.09X_{t-35} + 0.37X_{t-33} \\
X2 &= 0.13X_{t-48} + 0.39X_{t-34} + 0.30X_{t-39} + -0.16X_{t-28} + 0.01X_{t-30} \\
X3 &= -0.22X_{t-34} + 0.02X_{t-43} + -0.17X_{t-39} + -0.27X_{t-45} + 0.32X_{t-25}
\end{aligned}$$

$$\begin{aligned}
X4 &= 0.42X_{t-34} + 0.32X_{t-30} + -0.09X_{t-35} + 0.02X_{t-39} + -0.16X_{t-31} \\
X5 &= -0.25X_{t-46} + -0.13X_{t-27} + 0.39X_{t-29} + -0.10X_{t-48} + -0.13X_{t-45} \\
Y1 &= 0.01X_{t-31} + -0.09X_{t-39} + 0.35X_{t-48} + 0.53X_{t-29} + 0.02X_{t-48} \\
X2 &= 0.47X_{t-33} + 0.46X_{t-26} + 0.01X_{t-33} + 0.03X_{t-32} + 0.06X_{t-36} \\
X3 &= 0.03X_{t-31} + 0.05X_{t-47} + 0.51X_{t-34} + 0.32X_{t-30} + -0.10X_{t-38} \\
X4 &= 0.35X_{t-48} + -0.12X_{t-35} + -0.18X_{t-28} + 0.00X_{t-29} + 0.34X_{t-29} \\
X5 &= 0.07X_{t-38} + 0.02X_{t-36} + 0.40X_{t-41} + -0.26X_{t-39} + -0.25X_{t-48} \\
Y1 &= -0.12X_{t-32} + -0.21X_{t-29} + 0.02X_{t-43} + 0.56X_{t-40} + -0.09X_{t-28} \\
X2 &= -0.29X_{t-47} + 0.01X_{t-41} + 0.50X_{t-27} + -0.17X_{t-46} + 0.02X_{t-49} \\
X3 &= -0.19X_{t-47} + 0.01X_{t-45} + 0.35X_{t-25} + 0.34X_{t-32} + -0.10X_{t-36} \\
X4 &= 0.06X_{t-46} + 0.00X_{t-34} + 0.56X_{t-28} + -0.29X_{t-43} + -0.10X_{t-44} \\
X5 &= 0.37X_{t-44} + -0.18X_{t-35} + 0.00X_{t-26} + 0.00X_{t-38} + 0.44X_{t-31} \\
Y1 &= 0.01X_{t-39} + -0.22X_{t-29} + -0.29X_{t-35} + -0.12X_{t-41} + 0.36X_{t-41} \\
X2 &= 0.82X_{t-41} + 0.02X_{t-32} + 0.00X_{t-40} + 0.03X_{t-39} + -0.13X_{t-31} \\
X3 &= -0.13X_{t-49} + 0.78X_{t-42} + 0.03X_{t-39} + 0.06X_{t-45} + 0.00X_{t-49} \\
X4 &= 0.01X_{t-26} + 0.33X_{t-26} + 0.37X_{t-33} + 0.01X_{t-30} + -0.28X_{t-26} \\
X5 &= -0.29X_{t-34} + 0.00X_{t-43} + 0.01X_{t-37} + -0.20X_{t-32} + 0.49X_{t-38} \\
Y1 &= -0.19X_{t-39} + 0.02X_{t-27} + 0.01X_{t-42} + -0.29X_{t-45} + 0.50X_{t-44} \\
X2 &= -0.17X_{t-36} + -0.27X_{t-43} + 0.00X_{t-32} + 0.33X_{t-48} + -0.23X_{t-28} \\
X3 &= 0.00X_{t-32} + -0.29X_{t-43} + 0.59X_{t-28} + -0.10X_{t-45} + 0.02X_{t-49} \\
X4 &= 0.06X_{t-25} + -0.20X_{t-32} + -0.09X_{t-33} + 0.31X_{t-42} + 0.33X_{t-38} \\
X5 &= -0.24X_{t-27} + 0.32X_{t-37} + -0.28X_{t-29} + -0.13X_{t-35} + 0.03X_{t-46} \\
Y1 &= -0.08X_{t-41} + -0.33X_{t-30} + -0.37X_{t-35} + -0.02X_{t-30} + -0.20X_{t-32} \\
X2 &= -0.19X_{t-45} + -0.33X_{t-45} + -0.36X_{t-34} + -0.02X_{t-49} + -0.09X_{t-35} \\
X3 &= -0.07X_{t-46} + -0.30X_{t-31} + -0.01X_{t-43} + -0.39X_{t-45} + -0.23X_{t-48} \\
X4 &= -0.01X_{t-35} + -0.05X_{t-38} + -0.13X_{t-30} + -0.43X_{t-41} + -0.37X_{t-37} \\
X5 &= -0.28X_{t-48} + -0.07X_{t-47} + -0.23X_{t-27} + -0.01X_{t-28} + -0.41X_{t-40} \\
Y1 &= -0.53X_{t-35} + -0.00X_{t-35} + -0.05X_{t-39} + -0.07X_{t-35} + -0.34X_{t-47} \\
X2 &= -0.25X_{t-35} + -0.17X_{t-45} + -0.42X_{t-26} + -0.14X_{t-45} + -0.03X_{t-39} \\
X3 &= -0.02X_{t-30} + -0.33X_{t-31} + -0.09X_{t-47} + -0.48X_{t-28} + -0.07X_{t-25} \\
X4 &= -0.30X_{t-25} + -0.33X_{t-33} + -0.01X_{t-35} + -0.29X_{t-30} + -0.07X_{t-41} \\
X5 &= -0.45X_{t-45} + -0.50X_{t-34} + -0.00X_{t-36} + -0.00X_{t-46} + -0.04X_{t-26} \\
Y1 &= -0.06X_{t-38} + -0.01X_{t-30} + -0.22X_{t-40} + -0.28X_{t-40} + -0.43X_{t-36} \\
X2 &= -0.00X_{t-29} + -0.02X_{t-27} + -0.68X_{t-46} + -0.27X_{t-46} + -0.02X_{t-40} \\
X3 &= -0.37X_{t-36} + -0.34X_{t-45} + -0.15X_{t-42} + -0.11X_{t-44} + -0.02X_{t-36} \\
X4 &= -0.40X_{t-33} + -0.56X_{t-31} + -0.01X_{t-26} + -0.03X_{t-29} + -0.00X_{t-28} \\
X5 &= -0.02X_{t-36} + -0.31X_{t-35} + -0.32X_{t-45} + -0.02X_{t-42} + -0.34X_{t-49} \\
Y1 &= -0.10X_{t-30} + -0.18X_{t-31} + -0.28X_{t-29} + -0.07X_{t-48} + -0.38X_{t-38} \\
X2 &= -0.43X_{t-34} + -0.42X_{t-49} + -0.03X_{t-32} + -0.03X_{t-26} + -0.09X_{t-41} \\
X3 &= -0.08X_{t-30} + -0.19X_{t-28} + -0.26X_{t-42} + -0.12X_{t-25} + -0.35X_{t-32} \\
X4 &= -0.26X_{t-29} + -0.16X_{t-46} + -0.22X_{t-26} + -0.29X_{t-46} + -0.07X_{t-49} \\
X5 &= -0.04X_{t-26} + -0.35X_{t-37} + -0.00X_{t-44} + -0.34X_{t-46} + -0.26X_{t-42}
\end{aligned}$$

$$\begin{aligned}
Y1 &= -0.45X_{t-16} + -0.20X_{t-40} + -0.02X_{t-27} + -0.19X_{t-42} + -0.14X_{t-25} \\
X2 &= -0.02X_{t-48} + -0.00X_{t-35} + -0.45X_{t-43} + -0.50X_{t-44} + -0.03X_{t-28} \\
X3 &= -0.13X_{t-42} + -0.47X_{t-32} + -0.17X_{t-43} + -0.22X_{t-34} + -0.00X_{t-32} \\
X4 &= -0.33X_{t-35} + -0.28X_{t-27} + -0.11X_{t-32} + -0.02X_{t-39} + -0.28X_{t-33} \\
X5 &= -0.25X_{t-46} + -0.04X_{t-50} + -0.28X_{t-17} + -0.24X_{t-25} + -0.20X_{t-39}
\end{aligned}$$

$$\begin{aligned}
Y1 &= 0.09X_{t-33} + 0.07X_{t-41} + 0.31X_{t-42} + 0.30X_{t-30} + 0.22X_{t-36} \\
X2 &= 0.08X_{t-47} + 0.20X_{t-45} + 0.13X_{t-48} + 0.35X_{t-45} + 0.24X_{t-28} \\
X3 &= 0.00X_{t-29} + 0.10X_{t-46} + 0.28X_{t-34} + 0.43X_{t-31} + 0.19X_{t-47} \\
X4 &= 0.18X_{t-26} + 0.04X_{t-35} + 0.46X_{t-34} + 0.14X_{t-38} + 0.18X_{t-46} \\
X5 &= 0.49X_{t-29} + 0.16X_{t-48} + 0.25X_{t-46} + 0.04X_{t-47} + 0.05X_{t-39}
\end{aligned}$$

$$\begin{aligned}
Y1 &= 0.17X_{t-39} + 0.46X_{t-35} + 0.00X_{t-31} + 0.00X_{t-35} + 0.36X_{t-45} \\
X2 &= 0.03X_{t-32} + 0.21X_{t-35} + 0.36X_{t-33} + 0.14X_{t-45} + 0.25X_{t-37} \\
X3 &= 0.58X_{t-26} + 0.02X_{t-30} + 0.05X_{t-31} + 0.24X_{t-31} + 0.12X_{t-25} \\
X4 &= 0.08X_{t-48} + 0.36X_{t-25} + 0.02X_{t-48} + 0.40X_{t-33} + 0.13X_{t-30} \\
X5 &= 0.18X_{t-25} + 0.30X_{t-45} + 0.01X_{t-38} + 0.33X_{t-34} + 0.19X_{t-44}
\end{aligned}$$

$$\begin{aligned}
Y1 &= 0.04X_{t-25} + 0.02X_{t-38} + 0.21X_{t-44} + 0.00X_{t-39} + 0.18X_{t-28} \\
X2 &= 0.07X_{t-48} + 0.00X_{t-27} + 0.02X_{t-27} + 0.07X_{t-46} + 0.00X_{t-39} \\
X3 &= 0.05X_{t-25} + 0.25X_{t-28} + 0.10X_{t-49} + 0.27X_{t-38} + 0.09X_{t-28} \\
X4 &= 0.14X_{t-25} + 0.26X_{t-49} + 0.01X_{t-37} + 0.01X_{t-32} + 0.01X_{t-37} \\
X5 &= 0.05X_{t-34} + 0.05X_{t-27} + 0.16X_{t-38} + 0.07X_{t-29} + 0.01X_{t-31}
\end{aligned}$$

$$\begin{aligned}
Y1 &= 0.52X_{t-38} + 0.16X_{t-30} + 0.01X_{t-39} + 0.28X_{t-31} + 0.04X_{t-43} \\
X2 &= 0.13X_{t-33} + 0.15X_{t-34} + 0.44X_{t-42} + 0.15X_{t-49} + 0.13X_{t-46} \\
X3 &= 0.45X_{t-48} + 0.12X_{t-30} + 0.06X_{t-49} + 0.27X_{t-28} + 0.10X_{t-35} \\
X4 &= 0.00X_{t-31} + 0.57X_{t-29} + 0.01X_{t-26} + 0.34X_{t-46} + 0.07X_{t-31} \\
X5 &= 0.00X_{t-30} + 0.05X_{t-26} + 0.41X_{t-34} + 0.41X_{t-37} + 0.14X_{t-37}
\end{aligned}$$

$$\begin{aligned}
Y1 &= 0.28X_{t-31} + 0.23X_{t-36} + 0.10X_{t-39} + 0.10X_{t-40} + 0.29X_{t-42} \\
X2 &= 0.06X_{t-47} + 0.02X_{t-48} + 0.26X_{t-36} + 0.00X_{t-35} + 0.65X_{t-39} \\
X3 &= 0.33X_{t-46} + 0.14X_{t-42} + 0.00X_{t-32} + 0.53X_{t-32} + 0.00X_{t-29} \\
X4 &= 0.19X_{t-49} + 0.35X_{t-35} + 0.04X_{t-25} + 0.30X_{t-27} + 0.12X_{t-30} \\
X5 &= 0.27X_{t-30} + 0.36X_{t-46} + 0.31X_{t-27} + 0.05X_{t-50} + 0.00X_{t-47}
\end{aligned}$$

$$\begin{aligned}
Y1 &= 0.01X_{t-6} + 0.11X_{t-3} + -0.31X_{t-8} + -0.25X_{t-6} + -0.32X_{t-5} \\
X2 &= -0.21X_{t-13} + 0.17X_{t-2} + -0.31X_{t-9} + 0.09X_{t-14} + -0.22X_{t-3} \\
X3 &= -0.39X_{t-6} + 0.04X_{t-8} + -0.25X_{t-13} + -0.31X_{t-5} + 0.00X_{t-4} \\
X4 &= -0.22X_{t-6} + -0.37X_{t-1} + 0.03X_{t-8} + -0.37X_{t-3} + 0.01X_{t-14} \\
X5 &= 0.09X_{t-14} + -0.38X_{t-13} + -0.28X_{t-1} + 0.12X_{t-7} + 0.14X_{t-11}
\end{aligned}$$

$$\begin{aligned}
Y1 &= 0.03X_{t-1} + 0.00X_{t-11} + -0.22X_{t-10} + 0.52X_{t-11} + -0.22X_{t-7} \\
X2 &= -0.38X_{t-7} + 0.01X_{t-2} + 0.12X_{t-1} + 0.49X_{t-6} + -0.00X_{t-3} \\
X3 &= 0.02X_{t-13} + -0.32X_{t-11} + 0.02X_{t-2} + -0.32X_{t-10} + -0.32X_{t-3} \\
X4 &= 0.17X_{t-10} + -0.23X_{t-11} + 0.00X_{t-5} + 0.42X_{t-1} + 0.18X_{t-6} \\
X5 &= 0.40X_{t-6} + 0.13X_{t-5} + -0.34X_{t-5} + 0.12X_{t-4} + 0.01X_{t-1}
\end{aligned}$$

$$\begin{aligned}
Y1 &= -0.28X_{t-4} + 0.11X_{t-14} + -0.24X_{t-10} + 0.00X_{t-10} + -0.36X_{t-3} \\
X2 &= -0.25X_{t-14} + 0.02X_{t-1} + 0.03X_{t-8} + 0.03X_{t-4} + 0.67X_{t-13}
\end{aligned}$$

$X3 = -0.25X4_{t-3} + 0.16X3_{t-1} + 0.03X1_{t-12} + -0.30X0_{t-12} + -0.26X0_{t-2}$
 $X4 = -0.27X3_{t-12} + 0.51X1_{t-12} + 0.01X3_{t-4} + 0.12X0_{t-11} + 0.09X0_{t-13}$
 $X5 = -0.31X4_{t-7} + -0.31X0_{t-12} + -0.21X0_{t-4} + 0.17X0_{t-11} + 0.00X0_{t-10}$

 $Y1 = -0.27X4_{t-5} + -0.23X3_{t-3} + 0.00X0_{t-3} + 0.17X0_{t-3} + -0.33X0_{t-12}$
 $X2 = -0.38X1_{t-6} + 0.00X2_{t-12} + 0.03X4_{t-9} + 0.18X0_{t-1} + 0.41X0_{t-6}$
 $X3 = -0.40X2_{t-13} + 0.06X1_{t-8} + -0.33X3_{t-9} + 0.01X0_{t-4} + -0.20X0_{t-5}$
 $X4 = 0.14X2_{t-14} + 0.00X4_{t-3} + -0.22X4_{t-13} + 0.02X0_{t-2} + 0.62X0_{t-13}$
 $X5 = 0.05X2_{t-3} + -0.34X3_{t-7} + -0.27X4_{t-5} + -0.31X0_{t-12} + 0.04X0_{t-8}$

 $Y1 = 0.12X0_{t-9} + 0.11X1_{t-10} + 0.18X0_{t-12} + -0.23X3_{t-2} + -0.35X0_{t-2}$
 $X2 = 0.00X2_{t-6} + 0.43X0_{t-11} + 0.48X0_{t-14} + 0.08X4_{t-10} + 0.01X0_{t-4}$
 $X3 = 0.44X1_{t-5} + -0.21X4_{t-6} + 0.06X0_{t-12} + -0.22X1_{t-5} + 0.07X0_{t-1}$
 $X4 = -0.36X3_{t-2} + 0.02X1_{t-8} + -0.21X0_{t-10} + -0.39X1_{t-8} + 0.01X0_{t-12}$
 $X5 = 0.06X2_{t-14} + -0.40X4_{t-1} + 0.18X0_{t-6} + -0.23X4_{t-10} + 0.13X0_{t-8}$

 $Y1 = -0.12X0_{t-9} + -0.11X1_{t-10} + -0.18X3_{t-12} + -0.23X0_{t-2} + -0.35X0_{t-2}$
 $X2 = -0.00X2_{t-6} + -0.43X0_{t-11} + -0.48X0_{t-14} + -0.08X0_{t-10} + -0.01X0_{t-14}$
 $X3 = -0.44X1_{t-3} + -0.21X4_{t-6} + -0.06X3_{t-12} + -0.22X0_{t-5} + -0.07X0_{t-1}$
 $X4 = -0.36X3_{t-2} + -0.02X1_{t-8} + -0.21X0_{t-10} + -0.39X0_{t-8} + -0.01X0_{t-12}$
 $X5 = -0.06X2_{t-14} + -0.40X4_{t-1} + -0.18X4_{t-6} + -0.23X0_{t-10} + -0.13X0_{t-8}$

 $Y1 = -0.27X0_{t-4} + -0.02X3_{t-4} + -0.11X2_{t-7} + -0.35X0_{t-6} + -0.25X0_{t-9}$
 $X2 = -0.59X3_{t-12} + -0.04X3_{t-14} + -0.26X2_{t-3} + -0.07X3_{t-10} + -0.03X0_{t-5}$
 $X3 = -0.18X1_{t-4} + -0.24X4_{t-12} + -0.14X0_{t-12} + -0.19X0_{t-5} + -0.25X0_{t-9}$
 $X4 = -0.06X1_{t-8} + -0.48X3_{t-10} + -0.01X1_{t-9} + -0.01X0_{t-10} + -0.44X0_{t-6}$
 $X5 = -0.19X2_{t-13} + -0.04X3_{t-3} + -0.43X2_{t-13} + -0.07X0_{t-5} + -0.27X0_{t-6}$

 $Y1 = -0.00X1_{t-6} + -0.11X2_{t-6} + -0.45X4_{t-3} + -0.01X0_{t-3} + -0.43X0_{t-12}$
 $X2 = -0.21X1_{t-12} + -0.17X4_{t-12} + -0.00X3_{t-4} + -0.51X0_{t-3} + -0.11X0_{t-6}$
 $X3 = -0.10X0_{t-4} + -0.14X3_{t-2} + -0.20X2_{t-4} + -0.31X0_{t-15} + -0.25X0_{t-10}$
 $X4 = -0.27X4_{t-5} + -0.23X3_{t-3} + -0.00X0_{t-3} + -0.17X0_{t-3} + -0.32X0_{t-12}$
 $X5 = -0.38X1_{t-6} + -0.00X2_{t-12} + -0.03X4_{t-9} + -0.18X0_{t-1} + -0.41X0_{t-6}$

 $Y1 = -0.40X2_{t-13} + -0.06X1_{t-8} + -0.33X3_{t-9} + -0.01X0_{t-4} + -0.20X0_{t-5}$
 $X2 = -0.14X2_{t-14} + -0.00X4_{t-3} + -0.22X4_{t-13} + -0.02X0_{t-2} + -0.62X0_{t-13}$
 $X3 = -0.05X2_{t-3} + -0.34X3_{t-7} + -0.27X4_{t-5} + -0.31X0_{t-12} + -0.04X0_{t-8}$
 $X4 = -0.02X1_{t-7} + -0.33X2_{t-5} + -0.16X4_{t-11} + -0.46X0_{t-4} + -0.02X0_{t-8}$
 $X5 = -0.00X3_{t-1} + -0.03X3_{t-7} + -0.01X1_{t-8} + -0.51X0_{t-7} + -0.45X0_{t-14}$

 $Y1 = -0.28X1_{t-4} + -0.11X3_{t-14} + -0.24X3_{t-10} + -0.00X0_{t-10} + -0.36X0_{t-3}$
 $X2 = -0.25X0_{t-14} + -0.02X3_{t-1} + -0.03X3_{t-8} + -0.03X0_{t-4} + -0.67X0_{t-13}$
 $X3 = -0.25X4_{t-3} + -0.16X3_{t-1} + -0.03X1_{t-12} + -0.30X0_{t-12} + -0.26X0_{t-2}$
 $X4 = -0.27X3_{t-12} + -0.51X1_{t-12} + -0.01X3_{t-4} + -0.12X0_{t-11} + -0.09X0_{t-13}$
 $X5 = -0.31X4_{t-7} + -0.31X0_{t-12} + -0.21X0_{t-4} + -0.17X0_{t-11} + -0.00X0_{t-10}$

 $Y1 = 0.20X3_{t-10} + 0.18X1_{t-12} + 0.16X0_{t-9} + 0.33X0_{t-5} + 0.13X2_{t-13}$
 $X2 = 0.16X1_{t-14} + 0.37X0_{t-2} + 0.23X4_{t-13} + 0.02X0_{t-4} + 0.23X0_{t-8}$
 $X3 = 0.16X0_{t-16} + 0.03X4_{t-6} + 0.29X0_{t-2} + 0.23X0_{t-1} + 0.29X0_{t-13}$
 $X4 = 0.26X0_{t-6} + 0.45X4_{t-5} + 0.19X3_{t-14} + 0.10X0_{t-4} + 0.00X0_{t-4}$
 $X5 = 0.20X0_{t-12} + 0.48X0_{t-1} + 0.10X1_{t-11} + 0.10X0_{t-12} + 0.11X0_{t-12}$

$$\begin{aligned}
Y1 &= 0.00X3_{t-4} + 0.36X3_{t-5} + 0.36X0_{t-1} + 0.01X0_{t-14} + 0.26X0_{t-14} \\
X2 &= 0.38X1_{t-5} + 0.24X4_{t-10} + 0.16X5_{t-9} + 0.05X0_{t-7} + 0.17X0_{t-10} \\
X3 &= 0.03X3_{t-4} + 0.54X2_{t-14} + 0.33X0_{t-9} + 0.09X0_{t-8} + 0.01X0_{t-1} \\
X4 &= 0.07X1_{t-14} + 0.07X2_{t-9} + 0.61X2_{t-7} + 0.07X0_{t-3} + 0.18X0_{t-14} \\
X5 &= 0.01X1_{t-8} + 0.43X1_{t-13} + 0.41X1_{t-5} + 0.05X0_{t-14} + 0.10X0_{t-11} \\
\\
Y1 &= 0.20X4_{t-5} + 0.03X4_{t-11} + 0.29X2_{t-6} + 0.14X0_{t-2} + 0.34X0_{t-11} \\
X2 &= 0.54X4_{t-13} + 0.27X2_{t-1} + 0.07X0_{t-14} + 0.05X0_{t-14} + 0.07X0_{t-3} \\
X3 &= 0.28X0_{t-13} + 0.10X1_{t-11} + 0.45X4_{t-7} + 0.15X0_{t-7} + 0.02X0_{t-3} \\
X4 &= 0.05X3_{t-12} + 0.21X3_{t-9} + 0.32X1_{t-8} + 0.08X0_{t-11} + 0.35X0_{t-11} \\
X5 &= 0.22X1_{t-11} + 0.03X0_{t-5} + 0.29X4_{t-14} + 0.27X0_{t-4} + 0.20X0_{t-2} \\
\\
Y1 &= 0.01X4_{t-8} + 0.14X4_{t-7} + 0.40X1_{t-3} + 0.40X0_{t-9} + 0.06X0_{t-7} \\
X2 &= 0.40X1_{t-10} + 0.50X1_{t-8} + 0.03X0_{t-9} + 0.06X0_{t-4} + 0.01X0_{t-6} \\
X3 &= 0.11X4_{t-14} + 0.35X0_{t-14} + 0.49X2_{t-9} + 0.00X0_{t-14} + 0.05X0_{t-14} \\
X4 &= 0.01X4_{t-1} + 0.19X0_{t-8} + 0.36X2_{t-5} + 0.43X0_{t-1} + 0.01X0_{t-5} \\
X5 &= 0.30X0_{t-6} + 0.03X1_{t-5} + 0.16X2_{t-9} + 0.50X0_{t-8} + 0.01X0_{t-8} \\
\\
Y1 &= 0.22X1_{t-8} + 0.02X3_{t-3} + 0.13X3_{t-14} + 0.60X0_{t-11} + 0.03X0_{t-14} \\
X2 &= 0.19X4_{t-7} + 0.47X3_{t-4} + 0.07X0_{t-10} + 0.27X0_{t-3} + 0.00X0_{t-5} \\
X3 &= 0.00X2_{t-5} + 0.17X4_{t-7} + 0.25X4_{t-7} + 0.02X0_{t-14} + 0.56X0_{t-5} \\
X4 &= 0.14X0_{t-1} + 0.02X4_{t-10} + 0.08X4_{t-8} + 0.74X0_{t-8} + 0.02X0_{t-6} \\
X5 &= 0.40X2_{t-2} + 0.02X3_{t-10} + 0.00X3_{t-6} + 0.04X0_{t-12} + 0.54X0_{t-8} \\
\\
Y1 &= -0.09X4_{t-33} + 0.07X1_{t-41} + 0.31X3_{t-42} + 0.30X0_{t-30} + -0.22X0_{t-36} \\
X2 &= 0.08X1_{t-47} + -0.20X2_{t-45} + -0.13X1_{t-48} + 0.35X0_{t-45} + -0.24X0_{t-28} \\
X3 &= 0.00X2_{t-29} + -0.10X4_{t-46} + -0.28X0_{t-34} + 0.43X0_{t-31} + -0.19X0_{t-47} \\
X4 &= -0.18X3_{t-26} + 0.04X4_{t-35} + 0.46X0_{t-34} + -0.14X0_{t-38} + -0.18X0_{t-46} \\
X5 &= 0.49X0_{t-29} + -0.16X0_{t-48} + -0.25X0_{t-46} + 0.04X0_{t-47} + 0.05X0_{t-39} \\
\\
Y1 &= -0.17X3_{t-39} + 0.46X3_{t-35} + 0.00X3_{t-31} + 0.00X0_{t-35} + 0.36X0_{t-45} \\
X2 &= 0.03X1_{t-32} + -0.21X3_{t-35} + 0.36X1_{t-33} + -0.14X0_{t-45} + -0.25X0_{t-37} \\
X3 &= 0.58X1_{t-26} + 0.02X2_{t-30} + 0.05X3_{t-31} + -0.24X0_{t-31} + -0.12X0_{t-25} \\
X4 &= 0.08X4_{t-48} + 0.36X2_{t-25} + 0.02X1_{t-48} + 0.40X0_{t-33} + -0.13X0_{t-30} \\
X5 &= -0.18X4_{t-25} + -0.30X0_{t-45} + 0.01X1_{t-38} + 0.33X0_{t-34} + -0.19X0_{t-44} \\
\\
Y1 &= -0.25X1_{t-41} + 0.52X3_{t-28} + -0.22X3_{t-32} + 0.02X0_{t-39} + 0.00X0_{t-41} \\
X2 &= 0.44X0_{t-44} + -0.08X4_{t-42} + -0.17X2_{t-35} + -0.11X0_{t-40} + -0.20X0_{t-28} \\
X3 &= -0.22X4_{t-34} + -0.24X1_{t-33} + 0.42X0_{t-46} + 0.01X0_{t-37} + -0.11X0_{t-26} \\
X4 &= 0.03X1_{t-38} + 0.48X1_{t-37} + 0.06X0_{t-45} + -0.10X0_{t-28} + 0.34X0_{t-40} \\
X5 &= 0.32X4_{t-25} + -0.19X4_{t-41} + 0.00X4_{t-43} + -0.15X0_{t-28} + 0.34X0_{t-48} \\
\\
Y1 &= 0.52X3_{t-38} + -0.16X3_{t-30} + 0.01X4_{t-39} + -0.28X0_{t-31} + 0.04X0_{t-43} \\
X2 &= -0.13X3_{t-33} + -0.15X0_{t-34} + 0.44X1_{t-42} + -0.15X0_{t-49} + -0.13X0_{t-46} \\
X3 &= 0.45X1_{t-43} + -0.12X1_{t-30} + 0.06X4_{t-49} + -0.27X0_{t-28} + -0.10X0_{t-35} \\
X4 &= 0.00X2_{t-31} + 0.57X1_{t-29} + 0.01X4_{t-26} + 0.34X0_{t-46} + 0.07X0_{t-31} \\
X5 &= 0.00X3_{t-30} + 0.05X3_{t-26} + 0.41X0_{t-34} + 0.41X0_{t-37} + -0.14X0_{t-37} \\
\\
Y1 &= -0.28X0_{t-31} + -0.23X0_{t-36} + -0.10X1_{t-39} + -0.10X0_{t-40} + -0.29X0_{t-42} \\
X2 &= 0.06X4_{t-37} + 0.02X4_{t-48} + -0.26X4_{t-36} + 0.00X0_{t-35} + 0.65X0_{t-39} \\
X3 &= 0.33X1_{t-46} + -0.14X4_{t-42} + 0.00X2_{t-32} + 0.53X0_{t-32} + 0.00X0_{t-29}
\end{aligned}$$

$$\begin{aligned}
X4 &= -0.19X_{t-49} + 0.35X_{t-35} + 0.04X_{t-25} + -0.30X_{t-27} + -0.12X_{t-30} \\
X5 &= -0.27X_{t-30} + 0.36X_{t-46} + 0.31X_{t-27} + 0.05X_{t-50} + 0.00X_{t-47} \\
Y1 &= -0.23X_{t-42} + -0.25X_{t-35} + -0.07X_{t-41} + -0.09X_{t-35} + -0.37X_{t-33} \\
X2 &= -0.13X_{t-48} + -0.39X_{t-34} + -0.30X_{t-39} + -0.16X_{t-28} + -0.01X_{t-30} \\
X3 &= -0.22X_{t-34} + -0.02X_{t-43} + -0.17X_{t-39} + -0.27X_{t-45} + -0.32X_{t-25} \\
X4 &= -0.42X_{t-34} + -0.32X_{t-30} + -0.09X_{t-35} + -0.02X_{t-39} + -0.16X_{t-31} \\
X5 &= -0.25X_{t-46} + -0.13X_{t-27} + -0.39X_{t-29} + -0.10X_{t-48} + -0.13X_{t-45} \\
Y1 &= -0.01X_{t-31} + -0.09X_{t-39} + -0.35X_{t-48} + -0.53X_{t-29} + -0.02X_{t-48} \\
X2 &= -0.47X_{t-33} + -0.46X_{t-26} + -0.01X_{t-33} + -0.00X_{t-32} + -0.06X_{t-36} \\
X3 &= -0.03X_{t-31} + -0.05X_{t-47} + -0.51X_{t-34} + -0.32X_{t-30} + -0.10X_{t-38} \\
X4 &= -0.35X_{t-48} + -0.12X_{t-35} + -0.18X_{t-28} + -0.00X_{t-29} + -0.34X_{t-29} \\
X5 &= -0.07X_{t-38} + -0.02X_{t-36} + -0.40X_{t-41} + -0.26X_{t-39} + -0.25X_{t-48} \\
Y1 &= -0.12X_{t-32} + -0.21X_{t-29} + -0.02X_{t-43} + -0.56X_{t-40} + -0.09X_{t-28} \\
X2 &= -0.29X_{t-47} + -0.01X_{t-41} + -0.50X_{t-27} + -0.17X_{t-46} + -0.02X_{t-49} \\
X3 &= -0.19X_{t-47} + -0.01X_{t-45} + -0.35X_{t-25} + -0.34X_{t-32} + -0.10X_{t-36} \\
X4 &= -0.06X_{t-46} + -0.00X_{t-34} + -0.56X_{t-28} + -0.29X_{t-43} + -0.10X_{t-44} \\
X5 &= -0.37X_{t-44} + -0.18X_{t-35} + -0.00X_{t-26} + -0.00X_{t-38} + -0.44X_{t-31} \\
Y1 &= -0.01X_{t-39} + -0.22X_{t-29} + -0.29X_{t-35} + -0.12X_{t-41} + -0.36X_{t-41} \\
X2 &= -0.82X_{t-42} + -0.02X_{t-32} + -0.00X_{t-40} + -0.03X_{t-39} + -0.13X_{t-31} \\
X3 &= -0.13X_{t-39} + -0.78X_{t-42} + -0.03X_{t-39} + -0.06X_{t-45} + -0.00X_{t-49} \\
X4 &= -0.01X_{t-26} + -0.33X_{t-26} + -0.37X_{t-33} + -0.01X_{t-30} + -0.28X_{t-26} \\
X5 &= -0.29X_{t-34} + -0.00X_{t-43} + -0.01X_{t-37} + -0.20X_{t-32} + -0.49X_{t-38} \\
Y1 &= -0.19X_{t-39} + -0.02X_{t-27} + -0.01X_{t-42} + -0.29X_{t-45} + -0.50X_{t-44} \\
X2 &= -0.17X_{t-36} + -0.27X_{t-43} + -0.00X_{t-32} + -0.33X_{t-48} + -0.23X_{t-28} \\
X3 &= -0.00X_{t-32} + -0.29X_{t-43} + -0.59X_{t-28} + -0.10X_{t-45} + -0.02X_{t-49} \\
X4 &= -0.06X_{t-25} + -0.20X_{t-32} + -0.09X_{t-33} + -0.31X_{t-42} + -0.33X_{t-38} \\
X5 &= -0.24X_{t-27} + -0.32X_{t-37} + -0.28X_{t-29} + -0.13X_{t-35} + -0.03X_{t-46} \\
Y1 &= 0.08X_{t-41} + 0.33X_{t-30} + 0.37X_{t-35} + 0.02X_{t-30} + 0.20X_{t-32} \\
X2 &= 0.19X_{t-45} + 0.33X_{t-45} + 0.36X_{t-34} + 0.02X_{t-49} + 0.09X_{t-35} \\
X3 &= 0.07X_{t-46} + 0.30X_{t-31} + 0.01X_{t-43} + 0.39X_{t-45} + 0.23X_{t-48} \\
X4 &= 0.01X_{t-35} + 0.05X_{t-38} + 0.13X_{t-30} + 0.43X_{t-41} + 0.37X_{t-37} \\
X5 &= 0.28X_{t-48} + 0.07X_{t-47} + 0.23X_{t-27} + 0.01X_{t-28} + 0.41X_{t-40} \\
Y1 &= 0.53X_{t-35} + 0.00X_{t-35} + 0.05X_{t-39} + 0.07X_{t-35} + 0.34X_{t-47} \\
X2 &= 0.25X_{t-35} + 0.17X_{t-45} + 0.42X_{t-26} + 0.14X_{t-45} + 0.03X_{t-39} \\
X3 &= 0.02X_{t-30} + 0.33X_{t-30} + 0.09X_{t-47} + 0.48X_{t-28} + 0.07X_{t-25} \\
X4 &= 0.30X_{t-25} + 0.33X_{t-33} + 0.01X_{t-35} + 0.29X_{t-30} + 0.07X_{t-41} \\
X5 &= 0.45X_{t-45} + 0.50X_{t-34} + 0.00X_{t-36} + 0.00X_{t-46} + 0.04X_{t-26} \\
Y1 &= 0.20X_{t-45} + 0.00X_{t-43} + 0.02X_{t-45} + 0.00X_{t-46} + 0.23X_{t-34} \\
X2 &= 0.04X_{t-44} + 0.26X_{t-43} + 0.02X_{t-26} + 0.24X_{t-31} + 0.01X_{t-48} \\
X3 &= 0.04X_{t-28} + 0.19X_{t-40} + 0.06X_{t-39} + 0.02X_{t-39} + 0.00X_{t-46} \\
X4 &= 0.14X_{t-32} + 0.08X_{t-33} + 0.02X_{t-25} + 0.01X_{t-38} + 0.12X_{t-47} \\
X5 &= 0.01X_{t-44} + 0.19X_{t-35} + 0.01X_{t-45} + 0.15X_{t-45} + 0.00X_{t-27}
\end{aligned}$$

$Y_1 = 0.10X_3_{t-30} + 0.18X_1_{t-31} + 0.28X_3_{t-39} + 0.07X_0_{t-48} + 0.38X_0_{t-38}$
 $X_2 = 0.43X_0_{t-34} + 0.42X_0_{t-49} + 0.03X_0_{t-32} + 0.03X_0_{t-26} + 0.09X_0_{t-41}$
 $X_3 = 0.08X_1_{t-30} + 0.19X_4_{t-28} + 0.26X_1_{t-42} + 0.12X_0_{t-25} + 0.35X_0_{t-32}$
 $X_4 = 0.26X_1_{t-29} + 0.16X_3_{t-46} + 0.22X_4_{t-26} + 0.29X_0_{t-46} + 0.07X_0_{t-49}$
 $X_5 = 0.04X_3_{t-26} + 0.35X_4_{t-37} + 0.00X_2_{t-44} + 0.34X_0_{t-46} + 0.26X_0_{t-42}$

$Y_1 = 0.45X_0_{t-36} + 0.20X_0_{t-40} + 0.02X_2_{t-27} + 0.19X_0_{t-42} + 0.14X_0_{t-25}$
 $X_2 = 0.02X_4_{t-48} + 0.00X_2_{t-35} + 0.45X_3_{t-43} + 0.50X_0_{t-44} + 0.03X_0_{t-28}$
 $X_3 = 0.13X_4_{t-42} + 0.47X_1_{t-32} + 0.17X_0_{t-43} + 0.22X_0_{t-34} + 0.00X_0_{t-32}$
 $X_4 = 0.33X_2_{t-35} + 0.28X_3_{t-27} + 0.11X_2_{t-32} + 0.02X_0_{t-39} + 0.28X_0_{t-33}$
 $X_5 = 0.25X_3_{t-46} + 0.04X_2_{t-50} + 0.28X_2_{t-37} + 0.24X_0_{t-25} + 0.20X_0_{t-39}$

LIST OF REFERENCES

Bainbridge, L., "Mathematical Equations or Processing Routines," In J. Rasmussen & W. B. Rouse (Eds.), Human Detection and Diagnosis of System Failures, New York, 1981.

Brehmer, B., "Systems Design and the Psychology of Complex Systems," In J. Rasmussen and P. Zunde (Eds.), Empirical Foundations of Information and Software Science III, Plenum, New York, 1987.

Brehmer, B., "Dynamic Decision Making: Human Control of Complex Systems," Distributed Decision Making, v. 2, pp. 1-26, 1991b.

Brehmer, B. & Allard, R., "Real-time Dynamic Decision Making. Effects of Task Complexity and Feedback Delays," In J. Rasmussen, B. Brehmer & J. Leplat (Eds.), Distributed Decision Making: Cognitive Models for Cooperative Work, Chichester: Wiley, 1991a.

Brehmer, B. & Allard, R., "Feedback Delays in Real-Time Dynamic Decision Making," Uppsala Psychological Reports, 1991b.

Broadbent, D. E., Fitzgerald, P. and Broadbent, M. H. P., "Implicit and Explicit Knowledge in the Control of Complex Systems," British Journal of Psychology, v. 77, pp. 33-50, 1986.

Edwards, W., "Dynamic Decision Theory and Probabilistic Information Processing," Human Factors, v. 4, pp. 59-73, 1962.

Greene, D. P., "Automated Knowledge Acquisition: Overcoming the Expert System Bottleneck," Institute of Computer Information Systems, pp. 107-117, 1987.

Hogarth, R. M., "Beyond Discrete Biases: Functional and Dysfunctional Aspects of Judgemental Heuristics," Psychological Bulletin, v. 90, pp. 197-217, 1981.

Hogarth, R. M. and Makridakis, S. "The Value of Decision Making in a Complex Environment: An Experimental Approach to Management Science," v. 27, pp. 93-107, January 1981.

Kahneman, D. & Tversky A., "Prospect Theory: An Analysis of Decision under Risk," *Econometrica*, v. 47, pp. 263-291, 1979.

Kahneman, D. & Tversky A., "Judgment under Uncertainty: Heuristics and Biases," *Science*, v. 185, pp. 1124-1131, 1974.

Mackinnon, A. J. and Wearing, A. J., "Systems Analysis and Dynamic Decision Making," *Acta Psychological*, v. 58, pp. 159-172, 1985.

Makridakis, S. & Hibon, M. "Accuracy of Forecasting: An Empirical Investigation," *Journal of the Royal Statistical Review*, v. 46, pp. 255-278, 1978.

McLeod, J., "Computer Simulation: A Personal View," *Behavioral Science*, v. 34, no. 1, pp. 1-15, 1989.

Powers, W. T., "Feedback: Beyond Behaviorism," *Science*, v. 79, pp. 351-356, 1973.

Powers, W. T., "Quantitative Analysis of Purposive Systems: Some Spadework at the Foundations of Scientific Psychology," *Psychological Review*, v. 85, pp. 417-435, 1978.

Ramaprasad, A.. "On the Definition of Feedback," *Behavioral Science*, v. 28, no. 1, pp 4-13, 1983.

Rapoport, A., "Research Paradigms for the Study of Dynamic Decision Behavior," I. D. Wendt & C. Vlek (Eds.), *Utility, Probability and Human Decision Making*, Dordrecht: Reidel, 1975.

Simon, H. A., "The Science of the Artificial," Cambridge, Mass.: M.I.T. Press, 1969.

Sterman, J. D., "Modeling Managerial Behavior: Misperception of Feedback in a Dynamic Decision Making Experiment," *Management Science*, v. 35, no. 3, pp. 321-339, March 1989a.

Sterman, J. D., "Misperceptions of Feedback in Dynamic Decision Making," *Organizational Behavior and Human Decision Processes*, v. 43, pp. 301-335, 1989b.

Sterman, J. D., "Testing Behavioral Simulation Models by Direct Experiment," *Management Science*, v. 33, no. 12, pp. 1572-1592, December 1987.

Weiss, S. M. and Kulikowski, Casimir A., "Computer Systems
that Learn," Morgan Kaufmann Publisher's, 1991.

INITIAL DISTRIBUTION LIST

	No. Copies
1. Library, Code 52 Naval Postgraduate School Monterey, California 93943-5002	2
2. Administrative Sciences Department Naval Postgraduate School Attn: Professor Carl R. Jones, Code AS/JS	2
3. Administrative Sciences Department Naval Postgraduate School Attn: Professor Kishore Sengupta, Code AS/Se	2
4. Capt Spencer Rutledge III 1485 John G. Richards St. Camden, South Carolina 29020	2
5. Defense Technical Information Centers Cameron Station Alexandria, Virginia 22304-6145	2